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Review

A systematic literature review of spatio-temporal graph neural network models for time series forecasting and classification

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ABSTRACT

In recent years, spatio-temporal graph neural networks (GNNs) have attracted considerable interest in the field of time series analysis, due to their ability to capture, at once, dependencies among variables and across time points. The objective of this systematic literature review is hence to provide a comprehensive overview of the various modeling approaches and application domains of GNNs for time series classification and forecasting. A database search was conducted, and 366 papers were selected for a detailed examination of the current state-of-the-art in the field. This examination is intended to offer to the reader a comprehensive review of proposed models, links to related source code, available datasets, benchmark models, and fitting results. All this information is hoped to assist researchers in their studies. To the best of our knowledge, this is the first and broadest systematic literature review presenting a detailed comparison of results from current spatio-temporal GNN models applied to different domains. In its final part, this review discusses current limitations and challenges in the application of spatio-temporal GNNs, such as comparability, reproducibility, explainability, poor information capacity, and scalability. This paper is complemented by a GitHub repository at https://github.com/FlaGer99/SLR-Spatio-Temporal-GNN.git providing additional interactive tools to further explore the presented findings.

1. Introduction

In recent years, graph neural networks (GNNs) have emerged as a powerful class of artificial neural network models aimed at processing data that can be represented as graphs (Zheng et al., 2024c). GNNs are in fact particularly well-suited for a wide range of practical and engineering applications where data naturally lend themselves to be represented as graph structures, such as applications to transportation networks (Jiang & Luo, 2022), image analysis (Pradhyumna et al., 2021), classification of molecular structure (Ma & Lei, 2023), and natural language processing (Malekzadeh et al., 2021). The intuitive concept behind the GNN approach is that the nodes of a graph can be put in correspondence to objects or concepts, whereas the edges can be assumed to represent their mutual relationships (Scarselli et al., 2009). Data for these quantities can then be processed at once by a GNN model. GNNs can be used at three different levels, related to three distinct classes of problems: at graph-level, at edge-level, and at node-level (Zhou et al., 2020). In graph-level problems, the goal is to predict a property of a graph based on its entire structure, rather than on individual nodes or edges. For example, a molecule from a sample can be represented as a graph, and global properties of this molecule can be inferred from data coming from its entire structure in relation to the sample. In edge-level problems, the goal is to predict the presence or absence of edges between pairs of nodes. As an example, this task can be used in recommendation systems to predict potential connections between users and items on the basis of past interactions. In node-level problems, the goal is to predict the role or value of each node within a graph, in order to solve either a step-wise classification or a regression task. Noticeably, regression tasks can sometimes be put in the form of temporal “autoregressions”, that is, they can include time. When introduced, GNNs were at first applied to static datasets. The inclusion of time in GNN modeling has proven to have far-reaching consequences. Spatio-temporal GNNs have been applied to a wide range of time series tasks, including forecasting, classification, anomaly detection, and data imputation.

This review examines the available literature on the use of spatio-temporal GNNs for time series step-wise classification and futuredata

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forecasting, as these are the tasks most commonly addressed in the literature and best illustrate the current developments in spatio-temporal GNNs. The idea behind the use of GNNs for time series problems is that GNNs can be made capable of capturing complex relationships, both inter-variable (connections between different variables within a multivariate series) but also inter-temporal (dependencies between different points in time) at once (Jin et al., 2024). The inclusion of this capability in GNN models results in a characteristic *spatio-temporal* approach. Within this approach, the spatial dimension is related to the multivariate framework, where nodes typically correspond to different features of a multivariate time series at a given time step t, and edges to their relationships, and the temporal dimension is related to the temporal nature of the data. Spatio-temporal GNNs can thus be seen as a class of GNN models especially designed to handle data in both spatial and temporal dimensions at once. In a spatio-temporal graph, data in each node or edge can evolve over time, and the challenge is then to model their related dynamic interactions over time.

In the broader landscape of time series modeling, a variety of other approaches have been developed alongside spatio-temporal GNNs. Early statistical frameworks, such as ARIMA, and, more prominently, neural networks designed for sequential data, including RNNs, LSTMs, and GRUs, have been for a long time the standard solution for modeling temporal data. These architectures effectively capture short and medium term time dependencies, but struggle with very long sequences and with explicitly modeling interactions among multiple variables. The attention mechanism and the Transformer architecture, originally developed for handling long, static word sequences in Large Language Models (LLMs), were later adopted to better address long term dependencies in time series (Zhang et al., 2024g). Building on these architectural advances, and supported by the availability of modern GPU hardware, many experiments have been conducted. However, it remains unclear whether these highly parallelizable architectures are truly suitable for time series tasks (Tan et al., 2024). The development of LLMs has also stimulated a further line of research in time series modeling. LLMs, trained on massive text datasets for capturing general patterns in language, can then be adapted to a variety of downstream task, that is, as foundational models. Inspired by this approach, researchers have begun developing time series foundation models (TSFMs), designed to learn general representations from diverse temporal datasets (Liang et al., 2024b). These models, which do not necessarily use LLMs, are trained on large collections of time series to enable them to generalize effectively to new sequences.

All these approaches share the ability to model the dynamics of temporal data, and are inherently sequential models. What differentiates spatio-temporal GNNs from conventional machine learning, LLMs applied to dynamics, and TSFMs is how they handle the mutual relationships among features in multivariate time series. In TSFMs, these relationships are supposed to be learned end-to-end. In contrast, spatio-temporal GNNs explicitly prioritize these relationships. In the case of GNN models based on pre-defined static adjacency matrices, the inter-variable relationships are effectively "forced" into the model, like handcrafted features (which TSFMs could not be able to learn). As for GNNs using self-learned adjacency matrices, these more recent models are naturally biased toward explicitly identifying these relationships, offering a clearly interpretable representation of inter-dependencies.

Notwithstanding all the potential interest for such important features, to the best of our knowledge there is a lack of systematic literature reviews (SLRs) on spatio-temporal GNN models for time series applications. Most of the existing surveys are not SLRs, or they are not recent, or only focus on a limited number of application domains and specific issues not necessarily related to time series. A much broader view on the subject is nowadays necessary. For example, recent reviews focus on algorithmic features (Chen & Eldardiry, 2024; Chikwendu et al., 2024; Longa et al., 2023; Wu et al., 2020b), GNN characterization (Jin et al., 2024; Wu et al., 2025), specific fields (Fan et al., 2025; Jin et al., 2023b), and distributed training (Lin et al., 2023). Only two SLR on spatio-temporal GNNs were actually recently published, by Zeghina et al. (2024) and Fan et al. (2025). However, Zeghina et al. (2024) use a restrictive search query that limits the SLR to only 52 publications, whereas Fan et al. (2025) examine a broader collection of papers, but it is only focused on traffic flow prediction. In addition, Kumar et al. (2024) proposed a survey on spatio-temporal predictive modeling techniques for different domains. However, the authors approach the topic from a more general perspective, analyzing different machine learning models without placing too much emphasis on spatio-temporal GNNs. As an organized summary of these contributions, a list with a short description of the main reviews on spatio-temporal GNN models is provided in Table 1.

While most existing reviews focus on specific subfields, the present work takes a unique broader perspective. Its aim is to systematically collect and synthesize a wide range of publications on spatio-temporal GNNs for time series tasks, covering multiple application domains and methodological approaches. As a result, the number of articles included in this survey is larger than in more narrowly focused reviews. Although this approach results in a longer text, we hope it is able to provide a unique overview of the field, capturing both the diversity of applications and recent developments that cannot be fully appreciated in more specialized surveys.

The intention of the SLR presented here is therefore to: (i) offer a wide-ranging overview of spatio-temporal GNNs for time series classification and forecasting in different domains, (ii) assess whether their popularity stems from actual effectiveness, (iii) evaluate their efficacy and accuracy in different fields, (iv) collect results and benchmarks from the literature on GNN applications to support researchers in their work. In addition, to the best of our knowledge, this is the first review presenting comprehensive tables with all the results from the various models and benchmarks proposed in a highly fragmented literature. The tables presented in the paper are also available in the accompanying GitHub repository in an interactive format, enabling users to sort, filter, and explore the results of the various models. This synthesis and comparison of the results is performed by gathering data from the existing literature, without conducting any numerical experiment on data. Moreover, given the large number of selected papers, it was not feasible to include a description of all the proposed models. To compensate this limitation, we provide a description of the most commonly used benchmarks and the most accurate models within each group. In case, for more detailed descriptions of experimental setups and data pre-processing techniques, the reader is referred to the original papers. It is hoped that this collected and distilled knowledge can anyway become a valuable resource and reference for researchers.

During the development of this review, we formulated two sets of questions, one general and one specific, which are outlined below. The answers to the first set want to provide a general overview of the publications in the field, whereas the answers to the second set focus on specific aspects of the proposed spatio-temporal GNN models.
The general overview questions (GQs) are:

GQ1) **Trend**: What is the temporal trend of the number of publications on spatio-temporal GNNs? Is there a growing interest in GNNs?
GQ2) **Fields**: In which fields are GNN models most commonly applied?
GQ3) **Journals**: In which journals are the papers on GNNs published? Are these journals chosen because of the specific domain of application, or not?
GQ4) **Conferences**: What are the most prominent conferences where GNN research is presented?
GQ5) **Research groups**: Which are the most active research groups on GNNs?
GQ6) **Tools**: What tools (programming languages, libraries, frameworks) are used to implement the GNN models?
GQ7) **Fundings**: Did the authors of the papers receive public or private funding for their research?

The specific questions (SQs) are:

Table 1
Short description of main reviews on spatio-temporal GNN models. At the time of writing this SLR, articles marked with a ⋄ were only available as preprints.

Review	Description
(Wu et al., 2020b)	One of the first reviews on the use of GNNs in machine learning and data mining. It introduces a taxonomy that classifies GNN architectures into four categories: recurrent, convolutional, graph autoencoders, and spatial-temporal GNNs. The focus of this review is primarily on early GNN models, rather than applications on time series data.
(Zhou et al., 2020)	The authors outline a general design pipeline for GNN models, covering key aspects such as the graph structure, pooling techniques, loss function design, and components of the propagation module (including recurrent and convolutional operators, and skip connections). They present some applications of GNNs, including physical systems modeling, chemical analysis, text processing, image classification, recommendation systems, and analysis of other types of data.
(Jin et al., 2023b)	Review on the applications of spatio-temporal GNNs to predictive learning in urban computing. In the specific, the authors describe four methods for the construction of pre-defined graphs: topology-based, distance-based, similarity-based and interaction-based approaches. Then, they discuss various design strategies for spatio-temporal GNNs and their combination with some advanced learning frameworks, such as adversarial learning, continuous learning, and physics informed learning.
(Li et al., 2023i)⋄	The authors aim to provide a systematic review of spatio-temporal mining using GNNs. After providing an overview of the graph structure and the spatial and temporal components of GNNs, the authors describe some applications in fields such as transportation, disaster management, environment, power systems, and neuroscience. However, unlike our review, they do not outline the selection process of the papers or include detailed and comprehensive tables that cover datasets, benchmarks and results.
(Lin et al., 2023)	This review is specialized on distributed training of GNNs. It investigates optimization techniques used in this context, including parallel mini-batch generation, dynamic mini-batch allocation, mini-batch transmission pipelining, and parallel aggregation with edge partitioning.
(Longa et al., 2023)	The authors offer an overview of GNNs for temporal graphs. They describe supervised and unsupervised learning tasks on temporal graphs, and present a taxonomy of temporal GNNs that groups the model in snapshot-based and event-based approaches.
(Chen & Eldardiry, 2024)	One of the first reviews on the use of GNNs for time series modeling. The authors thoroughly describe a wide range of models for time series classification, forecasting, and anomaly detection, based either on recurrent/convolutional GNNs and attentional GNNs. Moreover, they provide a brief comparison of the models' performances in traffic forecasting and anomaly detection in water treatment.
(Chikwendu et al., 2024)	This survey provides an overview of graph neural architecture search, and explores methods for representing nodes, edges, and sub-graphs, which add context and semantics to graphs. The authors also describe some applications, including computer vision, brain networks, recommendation system, biomedical application, natural language processing, and traffic.
(Feng et al., 2024d)⋄	This survey examines 81 dynamic GNN models. It introduces a novel taxonomy that categorizes GNNs into discrete-time dynamic graphs and continuous-time dynamic graphs based on their structures, features, and dynamic modeling methods. In addition, the authors perform numerical experiments which evaluate 12 significant models on 6 graph datasets, which are not inherently related to time series.
(Jin et al., 2024)	The authors present a comprehensive review of GNNs for time series analysis, covering forecasting, classification, anomaly detection, and imputation. They categorize spatio-temporal GNNs according to their three main components: the spatial module, the temporal module, and the overall model architecture. Although they focus on the same topic as our SLR, they do not provide a detailed comparison of the results of existing models in the literature.
(Khemani et al., 2024)	The review discusses general concepts of GNNs, including architectures, techniques, datasets, applications, and challenges, offering a broad analysis that emphasizes these aspects without focusing specifically on time series analysis. It provides a brief description of papers in the literature, detailing application areas, datasets used, models applied, and performance evaluation.
(Kumar et al., 2024)	This SLR includes 200 papers from high-impact journals and prominent conferences on spatio-temporal predictive modeling techniques across different domains. Although its structure is similar to that of our review, its focus is broader and not specifically on spatio-temporal GNNs, as it also covers and discusses statistical and non-GNN machine learning models.
(Zeghina et al., 2024)	This SLR includes 52 papers on spatio-temporal GNNs across various application domains. Compared to our SLR, it covers a limited set of papers due to a restricted search query and it does not provide detailed and comprehensive tables of datasets, benchmarks, and model results.
(Capone et al., 2025)	This review provides an overview of recent spatio-temporal GNN models and classifies them as time-then-space (TTS), space-then-time (STT), and combined space-and-time (S&T) models. Compared to our SLR, this review is not systematic, it includes a limited number of papers, and it does not provide detailed quantitative comparisons of model performance across datasets.
(Fan et al., 2025)	This SLR covers 86 studies on the use of GNNs for traffic flow prediction. It examines data processing, model deployment, graph construction methods, and network architectures, discussing their respective strengths and weaknesses. However, unlike our review, its focus is on a single application domain.
(Wu et al., 2025)	This review offers a comprehensive survey of GNN models from the perspective of computation theory. In particular, the authors compare existing GNN models through various perspectives: time, memory, communication, parallelism, and execution.

SQ1) **Applications**: Which are the most studied applications of spatio-temporal GNNs? Are there differences in approaches and results across different application areas?
SQ2) **Graph construction**: Is the graph structure predetermined? If not, how do researchers define it?
SQ3) **Taxonomy**: Among the various taxonomy classes for GNNs, which are the most common? Are there some recurring mechanisms?
SQ4) **Benchmark models**: Which are the most commonly used benchmark models? Are they non-GNN machine learning models or also GNN models?
SQ5) **Benchmark datasets**: Which are the most commonly used benchmark datasets?
SQ6) **Modeling paradigms**: Which is the most common modeling paradigm? Is it modeling complex interacting systems, or modeling a system with multiple interacting quantities? Specifically, do graphs typically condense the relationships among multiple entities, or they describe different aspects of the same entity? In other words, is the used graph structure homogeneous or heterogeneous?
SQ7) **Metrics**: Which are the most common metrics used to assess the accuracy of a given model?

As the discussion will progress, the answers to both the general and the specific questions will be integrated in it. This will hopefully provide a comprehensive overview of the state-of-the-art of spatio-temporal GNN models. At the same time, a general overview of such GNN models will be assembled by highlighting similarities and differences between the approaches across different fields. In case of need of an even more detailed analysis of a specific discipline, or other aspects of GNN models, the reader is invited to consult the specialized reviews mentioned before (Bing et al., 2022; Capone et al., 2025; Chen & Eldardiry, 2024; Chikwendu et al., 2024; Fan et al., 2025; Feng et al., 2024d; Jin et al., 2023b, 2024; Khemani et al., 2024; Kumar et al., 2024; Li et al., 2023i; Lin et al., 2023; Longa et al., 2023; Shao et al., 2024; Wu et al., 2025, 2020b; Zeghina et al., 2024; Zhou et al., 2020).

The paper is organized as follows. After this Introduction, Section 2 illustrates the methodology used to collect the papers. Section 3 provides a general overview of the selected papers. Section 4 introduces some fundamental definitions and notions at the basis of spatio-temporal GNN models, and discusses their taxonomy and the determination of the graph structure. Section 5 is the core of this review. It explores the diverse domains of application of the spatio-temporal GNN models proposed in the selected papers for the identified domains. A discussion of

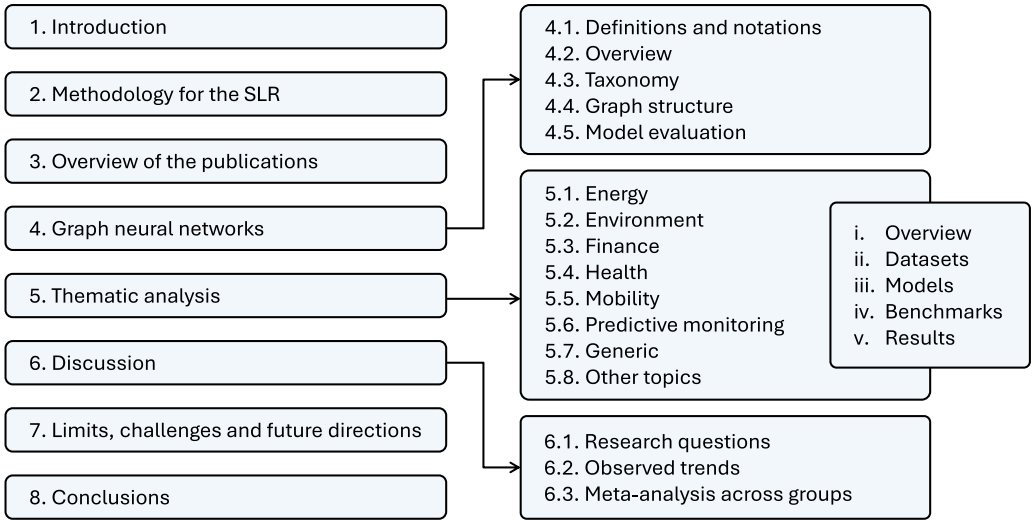


Fig. 1. Overview of the structure of the SLR.

the findings and the answers to the research questions mentioned above are provided in Section 6. Finally, limits, challenges and future research directions are presented in Section 7. Section 8 concludes the review. Appendix A provides a list of all papers included in this SLR, together with the year of publication, group they belong to, case study, and nature of the task (e.g., classification or forecasting). All links mentioned in the papers are included in this review. For the reader's convenience, links that no longer work at the time of submission are marked with a †. The overall structure of the paper is visually summarized in Fig. 1.

To maximize the accessibility and usability of the collected information, the paper is supported by a GitHub repository, available at https://github.com/FlaGer99/SLR-Spatio-Temporal-GNN.git, which complements the review with interactive resources. Beyond listing the 366 reviewed papers organized by groups, the repository offers interactive tables for sorting and filtering models by any metric, dynamic plots to visualize performance and trends, and tools to explore top-performing models and most common benchmarks. These features make it easy for readers to analyze, compare, and gain deeper insights from the collected data. We strongly encourage exploring the repository as an interactive complement to this paper, especially when examining the extensive and complex tables comparing model results, as it allows readers to easily sort and visualize the data.

2. Methodology for the systematic literature review

In order to conduct this SLR, four databases of primary importance were consulted: Scopus, IEEE Xplore, Web of Science, and ACM. These databases were chosen for their comprehensive coverage of academic and scientific literature, ensuring a broad and inclusive search across multiple disciplines.

Prior to commencing the literature search, some exclusion criteria were defined. First, papers from the current year 2025 were excluded because it has only just begun, hence the review will only cover the literature up to the end of year 2024. Second, only journal articles published in Q1 and Q2 journals, as ranked by the Scimago Journal Rank, and conference papers from A* and A venues, according to the ICORE conference rankings, were included. This selection was made to ensure that the analysis focused exclusively on high-quality, peer-reviewed research published in top-tier venues. Additionally, book chapters, workshops, and tutorials were excluded.

An advanced search query to be submitted to the databases was designed to capture the breadth of the topic while maintaining specificity. Its general form is `((''graph neural network'' OR gnn) AND (''time series'') AND (classification OR forecasting)` [1]. The first two elements of the query aim to restrict the pool of GNN models to the time series domain, and the second part focuses the search on classification and forecasting applications.

Overall, the selection process of the papers followed the multi-stage approach described below:

1. **Database search**: the search query was submitted to each of the four databases, and all records were imported into a csv file.
2. **Duplicate removal and venue filtering**: duplicate records were removed, along with publications from journals outside Q1–Q2 and conferences not ranked A* or A.
3. **Title and abstract screening**: the remaining records were screened by reading their titles and abstracts. Studies that at first sight did not meet the criteria were discarded.
4. **Full-text screening**: the full texts of the remaining papers were analyzed one by one, which led to a further assessment of eligibility.
5. **Data extraction**: relevant data and features were extracted from the included studies, and analyzed in order to better discuss the approach and present the most common datasets and models for each identified field.

A graphical representation of this selection process is provided in Fig. 2. A total of 2663 records were identified, 766 from Scopus, 258 from IEEE Xplore, 292 from Web of Science, and 1347 from ACM. After that, 1618 duplicates and publications from non top-tier venues were removed. Then, the titles and abstracts of the remaining 1045 records were manually evaluated to select the pertinent papers. Among these, 667 were discarded because they were considered outside the scope of this review, and 12 were discarded because they were not in English.

[1] Specific search queries for the different databases:

- Scopus: `TITLE-ABS-KEY((((''graph neural network'' OR gnn) AND (''time series'') AND (classification OR forecasting)) AND PUBYEAR < 2025.`
- IEEE Xplore: `((''graph neural network'' OR gnn) AND (''time series'') AND (classification OR forecasting).` Filters applied: 2000 – 2024.
- Web of Science: `((''graph neural network'' OR gnn) AND (''time series'') AND (classification OR forecasting).` Filters applied: 2000 – 2024.
- ACM: `[[All: ''graph neural network''] OR [All: gnn]] AND [All: ''time series''] AND [[All: classification] OR [All: forecasting]] AND [E-Publication Date: (01/01/2000 TO 12/31/2024)].`

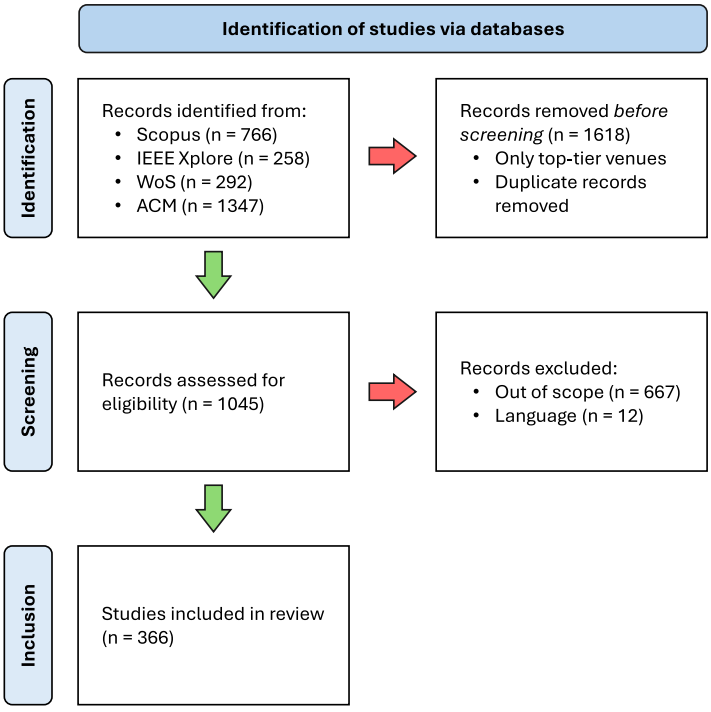


Fig. 2. PRISMA flowchart summarizing the identification and selection process, adapted from (Page et al., 2021). The flowchart is structured vertically into three key phases: identification (collection of records from databases, and removal of duplicates and non-top-tier venues), screening (assessment for eligibility and exclusion of out-of-scope studies), and inclusion (inclusion of papers in the review). The boxes on the right indicate the number of studies excluded at each stage.

As a result, 366 records were included in the review, comprising 262 journal papers and 104 conference papers. The complete list of selected paper can be found in Appendix A and in the accompanying GitHub repository.

Next, Section 3 provides an overview of the selected publications.

3. Overview of the publications

This section provides a comprehensive overview of the 366 selected papers. After their selection, the papers were grouped according to their domain of application, as better explained in the thematic analysis of Section 5. In the following, some overall bibliographic information about the reviewed articles is presented.

Fig. 3 presents a stacked column chart showing the number of journal and conference publications over time, broken down by research group. The height of each column represents the total number of publications per year, while the colored segments represent contributions from each group. A clear upward trend can be observed over time, especially in journal papers, reflecting an increasing interest in spatio-temporal GNN models across various fields, since 2020. The groups that experienced the most significant increase are “Environment”, “Generic”, “Mobility”, and “Predictive monitoring”, among which “Generic” and “Mobility” stand out in terms of both number of publications and the novelty of their contributions. For more details, see also the group numerosity reported in Table 2.

The catalog of the publication sources indicates that, in the studies period, 131 different Q1 and Q2 journals have published articles on GNN models for time series forecasting or classification. Table 3 lists the journals with more than 5 published papers.

The diversity of the journals indicates a vast range of potential applications for spatio-temporal GNN models in different fields. This suggests that researchers often select journals based on the specific domain of application. This allows them to reach targeted audiences, and contribute within their respective fields. Such diversity also underlines the interdisciplinary nature of GNNs research, clearly spanning multiple domains.

Table 2
Pivot table illustrating the number of publications by year and group (journal and conference papers combined).

Field / Year	2020	2021	2022	2023	2024	Total
Energy	1	1	6	5	20	**33**
Environment	0	2	4	22	15	**43**
Finance	0	0	5	6	3	**14**
Health	1	3	5	7	7	**23**
Mobility	11	6	24	27	34	**102**
Predictive monitoring	0	2	4	12	22	**40**
Generic	4	7	11	28	27	**77**
Other	0	4	5	14	11	**34**
Total	**17**	**25**	**64**	**121**	**139**	**366**

Table 3
Journals with more than 5 published paper.

Journal	Papers
IEEE Access	14
ACM Transactions on Knowledge Discovery from Data	9
Knowledge-Based Systems	9
Applied Intelligence	8
IEEE Transactions on Instrumentation and Measurement	8
ACM Transactions on Intelligent Systems and Technology	7
Expert Systems with Applications	7
IEEE Transactions on Knowledge and Data Engineering	7
Applied Energy	6
IEEE Transactions on Industrial Informatics	6
IEEE Transactions on Intelligent Transportation Systems	6
Sensors	6

As for ranked A* and A conference venues, 18 different venues have hosted publications on GNN models for time series forecasting or classification. The conference venues with 5 or more papers are listed in Table 4.

Fig. 4 shows a pie chart of how corresponding authors are distributed among different countries. This visualization provides an overview of

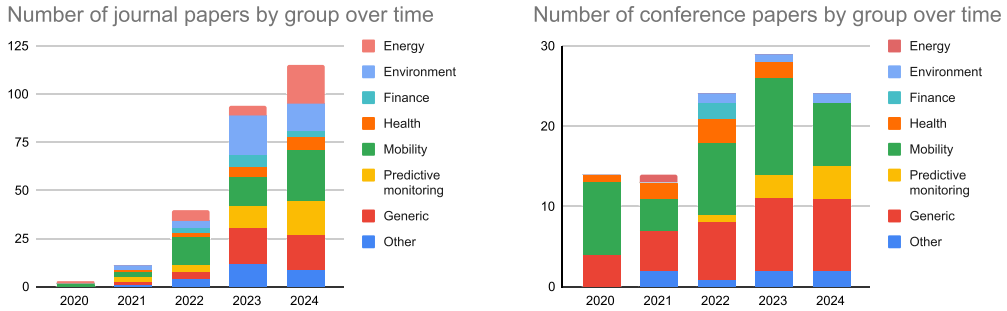


Fig. 3. Number of journal and conference papers over time across the different groups.

Table 4
Conference venues with more than 5 published paper.

Conference venue	Papers
ACM Int. Conf. on Information and Knowledge Management (CIKM)	30
ACM Int. Conf. on Knowledge Discovery and Data Mining (KDD)	18
ACM Int. Conf. on Advances in Geographic Information Systems (SIGSPATIAL)	11
Advances in Neural Information Processing Systems (NeurIPS)	7
Int. Conf. on Machine Learning (ICML)	5

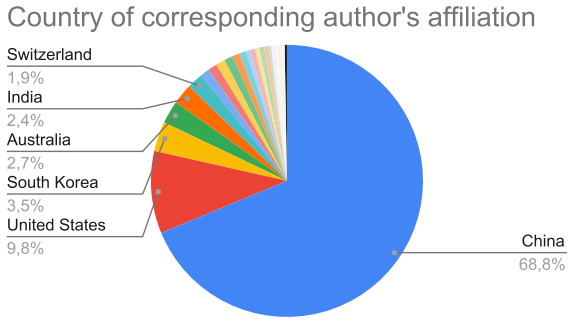


Fig. 4. Pie chart of the distribution of corresponding authors in different countries.

the global distribution of research activities. Nearly 70 % of the authors are affiliated with institutions based in China.

In order to examine the degree of collaboration among researchers, a co-authorship network was generated by using the VOSviewer software (Van Eck & Waltman, 2010). In this network, authors are represented as nodes, and co-authorships as connections, revealing clusters of researchers who frequently collaborate. Fig. 5 shows the complete network, while Fig. 5(b) provides an enlarged view of two selected clusters.

In the figures, the color of each node corresponds to the author's average publication year, allowing the temporal evolution of research groups to be visualized. From the complete network in Fig. 5, two main insights emerge. First, the large number of clusters indicates a highly fragmented research community, with many small, relatively independent groups. Second, the color of the nodes indicates that some groups were active primarily in earlier years and have since faded, while others have emerged more recently, as indicated by the yellow color. Additionally, several authors appear in multiple clusters, reflecting collaborations that span different groups over time, as also shown in Fig. 5(b).

Additional figures and analyses of trends in the collected papers are available on our GitHub repository.

4. Graph neural networks

This section introduces some fundamental definitions and notions at the basis of the study of time series with spatio-temporal GNNs.

4.1. Definitions and notations

Definition 1 (Time series). A time series is a sequence of data points indexed by timestamps, that here are assumed to be equispaced. An equispaced univariate time series of length T is a sequence of scalar observations collected over time, denoted as $\vec{x}_t \in \mathbb{R}^T$. An equispaced multivariate time series of length T is a sequence of D-dimensional vector observations collected over time, denoted as $\vec{x}_t \in \mathbb{R}^{D\times T}$.

Definition 2 (Graph). A graph $\mathcal{G}$ is a pair of finite sets $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \{v_1, \dots, v_n\}$ is a set of n nodes (also called vertices) and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ is the set of connecting edges. In an undirected graph each edge is an unordered pair of nodes $\{v_i, v_j\}$, while in a directed graph the edges have an orientation, and correspond to ordered pairs (v_i, v_j). When an edge (v_i, v_j) or $\{v_i, v_j\}$ exists, the nodes v_i and v_j are called adjacent.

Definition 3 (Spatio-temporal graph). A spatio-temporal graph is a 4-tuple $\mathcal{G} = (\mathcal{V}_t, \mathcal{E}_t, \mathcal{X}_t, \mathcal{T})$, where $\mathcal{T} = \{t_1, \dots, t_T\}$ is a set of T timestamps t, $\mathcal{V}_t = \{v_1(t), \dots, v_{n_t}(t)\}$ is a set of n_t nodes representing spatial entities at time t, $\mathcal{E}_t = \{e_1(t), \dots, e_{m_t}(t)\}$ is a set of m_t edges representing the relationships between nodes at time t, $\mathcal{X}_t = \{x_{v_1}(t), \dots, x_{v_{n_t}}(t)\} \cup \{r_{e_1}(t), \dots, r_{e_{m_t}}(t)\}$ is a set of attributes associated with nodes and edges (x_{v_i} and r_{e_i} are respectively the attributes of node v_i and edge e_i, and can be either scalars of vectors) at time t. Notice that the sets of nodes and edges can change over time, as well as the set of attributes $\mathcal{X}_t$.

Hereafter, the time index will be dropped to indicate graphs not necessarily changing in time, i.e., not necessarily spatio-temporal.

Definition 4 (Adjacency matrix). The adjacency matrix $\mathcal{A}$ of a graph $\mathcal{G}$ with $|\mathcal{V}| = n$ nodes is a $n \times n$ square matrix, with $\mathcal{A}_{ij}$ specifying the number of connections from node v_i to node v_j for $i, j = 1, \dots, n$. Here it is assumed that a graph cannot have more than one edge between any two nodes, so $\mathcal{A}_{ij}$ can only be 0 or 1 depending on whether there is a connection or not.

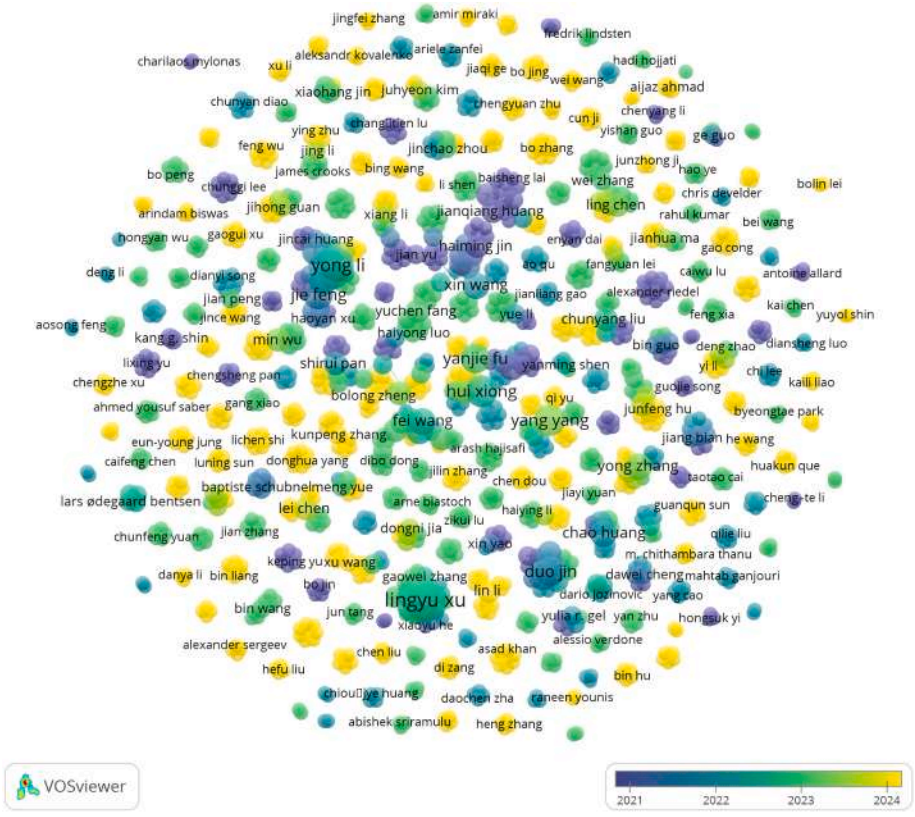
Definition 5 (Degree matrix). The degree matrix $\mathcal{D}$ of a graph with $|\mathcal{V}| = n$ nodes is a diagonal matrix whose entries are given by the degree of each node, i.e., the number of edges attached to the node. In formulas, its diagonal elements are given by

$$\mathcal{D}_{ii} = \sum_j \mathcal{A}_{ij}. \tag{1}$$

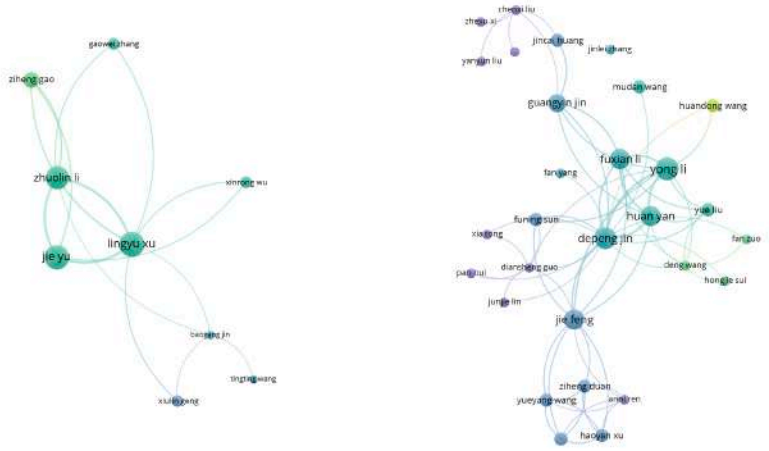
4.2. Overview of graph neural networks

Given a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, a GNN model (not necessarily spatio-temporal) aims to generate an embedding (i.e., a vector of real entries) for each node in the graph. An overall graph embedding consists of representing a graph in a space of chosen dimension, while preserving its structural information.

The notion of GNN was initially proposed by Gori et al. (2005) and Scarselli et al. (2009) as an architecture designed to implement a function that maps a graph $\mathcal{G}$ with n nodes into an m-dimensional Euclidean



(a) Map of the complete collaboration network.



(b) Enlargement on two different clusters.

Fig. 5. Network of collaboration between researchers, created using VOSviewer software.

space. Noticeably, this definition was intended in general for graph data, not specifically time-dependent data, which is the focus of this SLR. In Scarselli et al. (2009) the target node's embedding was learned in two steps. First, neighbor information is iteratively propagated with fixed weights within the graph until a stable fixed point is reached (whose existence is guaranteed under certain assumptions by Banach's fixed point theorem). Second, errors on targets are propagated back across the graph. Notice that in this setup, propagation is performed in "internal time", not in "clock time". More in general, the calculation of node embeddings is quite complex, and over time many other methods have been developed. These methods are based on different architectures and sophisticated aggregation mechanisms. Based on these aggregating mechanisms, a taxonomy of GNN models with different classes has been defined. In this review, we adopt a taxonomy for the discussed spatio-temporal GNNs similar to the one proposed by Chen and Eldardiry (2024). More details about that will be given in Subsection 4.3.

4.3. Spatio-temporal GNNs and their taxonomy

A large part of the research on spatio-temporal GNNs is focused on multivariate time series, as they can be naturally abstracted into spatio-temporal graphs, as depicted in Fig. 6. In this context, nodes usually correspond to different variables at a given time step, and edges represent relationships between variables.

This specific form of spatio-temporal modeling assumes that the feature information of a node depends on both its own historical values and on the historical data from its neighboring nodes (Zeghina et al., 2024). Notice that once the graph structure is given, information is propagated

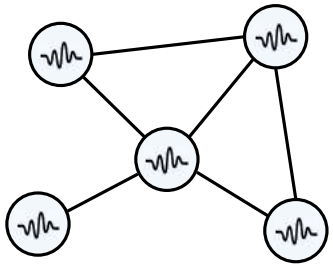


Fig. 6. Representation of a spatio-temporal graph. Here, each node has a dynamic feature, given by the points of the time series.

(in "internal time") within it until the output is obtained, as better explained in the following. Our discussion will build up from this perspective.

When it comes to the development of a spatio-temporal GNN model, there are two primary approaches: one that handles spatial and temporal substructures in separate blocks, and another that integrates and processes these two substructures at once (Zeghina et al., 2024). These approaches are implemented by means of modules that are purely spatial, purely temporal, or hybrid combinations of the two. These modules can then be organized into a series of blocks, thus creating the sought spatio-temporal GNN model.

In the taxonomy of spatio-temporal GNNs used in this review, the focus is exclusively on the description of the spatial module that propagates the information within the nodes at fixed time t (not explicitly included in the following equations for simplicity), which, in the reviewed literature, is a fundamental aspect that differentiates one GNN model from another. Based on the mechanism at the basis of the information propagation in the graph at a given time step, spatio-temporal GNNs can be further classified as recurrent GNNs, convolutional GNNs, and attentional GNNs, as represented in Fig. 7 and discussed in the following. These classes are not mutually exclusive, as some models may fit into hybrid categories. In addition, these classes are not fully exhaustive of the variety of available models, as there may be models that do not align with any of the existing categories. However, for the purpose of this review, the taxonomy discussed above will be considered sufficient.

Recurrent GNNs. Recurrent GNN modeling mainly proceeds from the results of early studies on GNNs, where the node embeddings are generated by iteratively propagating neighbor information until a stable fixed point is reached. The iterative equation for the calculation of the embedding (or hidden state) of node u has the form

$$h_u^{(k)} = f\left(x_u, \{x_v, r_{(u,v)}, h_v^{(k-1)} \mid v \in \mathcal{N}(u)\}\right), \tag{2}$$

where k is the index related to iteration (hence running on "internal time"), f is a parametric trainable function, x_u is the attribute associated to node u, $r_{(u,v)}$ is the weight of the edge (u, v) between the nodes u and v, $\mathcal{N}(v)$ denotes the neighborhood of node v, and the initial hidden states $h^{(0)}$ are usually randomly initialized. As detailed in the seminal work by Scarselli et al. (2009), which introduced recurrent GNNs, in order to ensure the convergence of Eq. (2) it is necessary that the iterative function f is a contraction mapping.

Convolutional GNNs. Convolutional GNNs are closely related to recurrent GNNs. They were introduced by Kipf and Welling (2017). Unlike recurrent GNNs, which apply the same iterative contraction mapping f until an equilibrium is reached, convolutional GNNs can use different parameters at each updating step, by stacking multiple graph convolutional layers to extract the node embeddings (Wu et al., 2020b). Noticeably, as the number of convolutional layers increases, the convolutional perceptual field expands, and a more abstract representation of information is thus obtained (Chen et al., 2024a).

A basic form for the equation for the k^{th} layer of a convolutional GNN with n nodes is

$$H^{(k)} = f_k\left(\tilde{\mathcal{A}} H^{(k-1)} \Theta_{k-1}\right), \quad \tilde{\mathcal{A}} = \hat{D}^{-\frac{1}{2}} \hat{\mathcal{A}} \hat{D}^{-\frac{1}{2}}, \quad \hat{\mathcal{A}} = \mathcal{A} + I, \quad \hat{D}_{ii} = \sum_j \hat{\mathcal{A}}_{ij}, \quad H^{(0)} = X, \tag{3}$$

where f_k represents the convolutional operation performed at layer $k \in \{1, \dots, K\}$ (with K typically kept small to prevent issues like oversmoothing (Giraldo et al., 2023)), $\mathcal{A} \in \mathbb{R}^{n \times n}$ is the adjacency matrix, $I \in \mathbb{R}^{n \times n}$ is the identity matrix (used to add self-loops in the adjacency matrix $\mathcal{A}$), $\hat{D} \in \mathbb{R}^{n \times n}$ is the diagonal degree matrix associated to $\hat{\mathcal{A}}$, $H^{(k)} \in \mathbb{R}^{n \times d_k}$ are the d_k-dimensional node embeddings $h_v^{(k)}$ of the entire graph produced by the k^{th} layer, $X \in \mathbb{R}^{n \times d_0}$ is the collection of all node attributes x_v of the entire graph, and $\Theta_k \in \mathbb{R}^{d_{k-1} \times d_k}$ is a trainable weight matrix for the k^{th} layer (Chen & Eldardiry, 2024). The mechanism of node embedding generation from Eq. (3) is illustrated in Fig. 8(b), where it is put in contrast with the mechanism of a recurrent GNNs, shown in Fig. 8(a).

Attentional GNNs. In attentional GNNs, the aggregation process uses the attention mechanism (Vaswani et al., 2017) to combine node features. The equations to compute the node embedding h_u of layer $k+1$ from the embeddings of layer k for each node u are

$$z_u^{(k)} = W_k h_u^{(k)}, \tag{4a}$$

$$\epsilon_{uv}^{(k)} = \text{LeakyReLU}\left(\vec{a}^{(k)^\top} \left(z_u^{(k)} \,||\, z_v^{(k)}\right)\right), \tag{4b}$$

$$\alpha_{uv}^{(k)} = \frac{\exp\left(\epsilon_{uv}^{(k)}\right)}{\sum_{w \in \mathcal{N}(u)} \exp\left(\epsilon_{uw}^{(k)}\right)}, \tag{4c}$$

$$h_u^{(k+1)} = f\left(\sum_{v \in \mathcal{N}(u)} \alpha_{uv}^{(k)} z_v^{(k)}\right). \tag{4d}$$

Eq. (4a) represents a learnable linear transformation of the node embedding $h_u^{(k)}$ using the trainable weight matrix W_k of layer k. Eq. (4b) computes a pairwise masked attention score between nodes u and v. This is done by applying the concatenation operation $||$ to the vectors $z_u^{(k)}$ and $z_v^{(k)}$, then calculating a dot product of the concatenation with a learnable weight vector $\vec{a}^{(k)}$, and finally applying the LeakyReLU nonlinearity. The quantity ϵ_{uv} indicates the importance of the features of node v to node u. The term "masked" refers to the fact that ϵ_{uv} are computed for neighboring nodes only. Eq. (4c) normalizes the attention score through the softmax function in order to make the α_{uv} comparable across different nodes. Finally, Eq. (4d) computes the embedding $h_u^{(k+1)}$ of the next layer by aggregating the information in neighboring nodes, weighted by the attention scores (Veličković et al., 2018). Graph attention networks can in addition use a multi-head attention mechanism to stabilize the learning process of self-attention. In practice, the node updating operation in graph attention networks is a generalization of the traditional averaging or max-pooling of neighboring nodes, which allows each node to compute a weighted average of its neighbors and identify the most relevant ones (Brody et al., 2022).

As anticipated, the taxonomy discussed so far focuses only on the propagation mechanisms of the spatial component. However, spatio-temporal GNNs typically consist of a stack of spatial, temporal, or also hybrid modules, each one with distinct roles. The function of these modules is detailed hereafter.

The spatial module is responsible for propagating information between nodes, thereby enabling the analysis of cross-sectional interdependencies between different variables. As previously discussed in the description of the mechanisms underlying the assumed taxonomy, the spatial module aggregates information starting from immediate neighboring nodes and extends it outward, thereby capturing also the influence of distant nodes. This spatial operation cannot directly account for temporal information. In contrast, the temporal module, often based on architectures such as LSTM, GRU, or self-attention, focuses on the

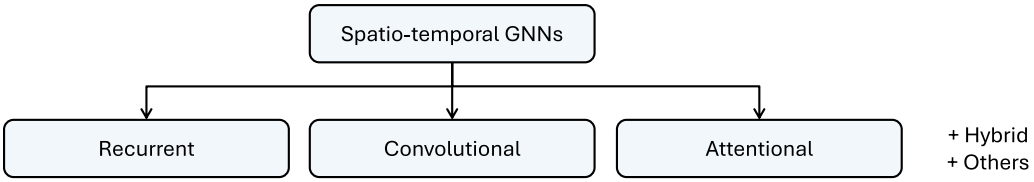
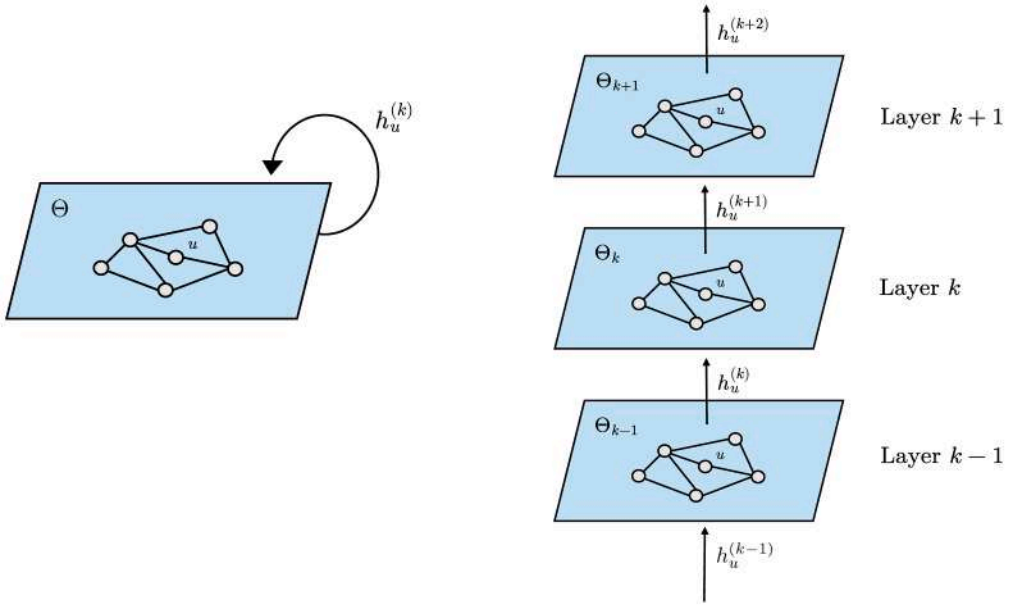


Fig. 7. Taxonomy of the spatial component of spatio-temporal GNNs, categorizing models into recurrent, convolutional, and attentional.



(a) Recurrent GNNs use the same graph recurrent layer in the iterative generation of the node embeddings. Here Θ represents the weights of the parametric trainable function f.

(b) Convolutional GNNs use different graph convolutional layers in the generation of the node embeddings.

Fig. 8. Comparison of the node embedding generation mechanisms in a recurrent GNN (left panel) and a convolutional GNN (right panel).

evolution of data over time, independently from cross-sectional node interactions. When these different modules are stacked together, spatial and temporal information end up to be used simultaneously, although they are processed in separate modules. This occurs because the computation of each node state is influenced by both spatial and temporal information. This combined approach allows the spatio-temporal GNN model to be a powerful architecture able to effectively capture at the same time both spatial relationships and temporal dynamics.

4.4. Determination of the graph structure

A crucial issue when dealing with spatio-temporal GNNs for time series tasks is the determination of the graph structure, i.e., the connectivity of the nodes. The type of spatial information captured by the graph can vary widely across domains. For instance, in traffic networks, nodes often represent sensors or intersections, and edges correspond to actual roads or physical connections. In contrast, in domains such as healthcare or finance, nodes may represent patients, brain regions, or financial instruments, and edges encode correlations, interactions, or other relational information. This variability across datasets highlights the importance of carefully designing the graph structure to reflect the spatial relationships relevant to each domain. The specific choices made in different application areas are discussed in the corresponding subsections of this review.

Namely, some time series datasets come by their own nature with a pre-defined graph structure (e.g., a road network for traffic datasets), whereas some others do not. When a natural graph structure is available, it helps the model capture the underlying dynamics more effectively. When it is not directly available, it must be defined by the user in some way (based on domain knowledge or some metrics), or determined by some algorithm (such as visibility graphs Lacasa et al., 2008; Wang et al., 2023c; Zeinalipour & Gori, 2023), or learned by the model itself.

Once the graph structure is determined, it is necessary to define the weighted graph adjacency matrix, which is a generalization of the graph adjacency matrix $\mathcal{A}$ whose entries are given by the edge weights of the graph. The edge weights can be defined *a priori* by the user, or again, learned by the model itself based on a pre-defined architecture. In the first case, the edge weights are assigned based on some pre-defined metrics or criteria chosen by the user, for example by the spatial distance between the sites, or by similarity measures. In the latter case, the weights are continuously adjusted throughout training as the model keeps learning from the data.

In the following, we present a concise overview of the most common techniques for defining graph structures.

Pre-defined graphs are typically generated based on prior knowledge and specific metrics. These methods for the construction of the graphs typically rely on distance or similarity information. As for location-based techniques, they utilize geographical coordinates (latitude and the longitude) of the nodes to calculate the distance between them (e.g., using haversine or geodesic distance). This distance information is then used to determine the edge weights with techniques such as the thresholded

Gaussian kernel (which applies a negative exponential function to the distance), weighted k-NN, or reversed MinMax. As for similarity-based techniques instead, they rely on similarity (or dissimilarity) of signal data. These techniques include methods such as correlation, cosine similarity, dynamic time warping (DTW), maximum information coefficient (MIM), or transfer entropy. In general, no single approach stands out as a clear winner, and performance should be evaluated on each dataset. For references and a more detailed explanation of these and other techniques for constructing pre-defined structures, see Bloemheuvel et al. (2023a).

As for automatic graph structure learning techniques, a distinction can be made between models that rely on pre-defined graph structures (sometimes referred to as supplementary graph structure learning models), and those that learn the graph structure entirely from scratch. Two notable examples from Wu et al. illustrate these approaches.

The first example is Graph WaveNet (GWN) (Wu et al., 2019), which constructs a self-adaptive adjacency matrix A using two randomly initialized learnable node embedding matrices E_1 and E_2 as:

$$A = \text{softmax}\big(\text{ReLU}\big(E_1\, E_2^{\top}\big)\big)\,, \tag{5}$$

where E_1 and E_2 correspond to the source and target node embeddings, respectively. Their multiplication represents the spatial dependency weights between source nodes and target nodes. In the original work, these learned hidden graph dependencies are combined with a pre-defined graph structure. The authors note that when such a structure is unavailable, the self-adaptive adjacency matrix alone can be used to model hidden spatial dependencies.

As a second example, which overcomes the reliance on a pre-defined graph, the same authors proposed the MTGNN model (Wu et al., 2020c), which extracts uni-directional relationships from node embeddings as follows:

$$\begin{aligned}
M_1 &= \tanh(\eta\, E_1\Phi_1)\\
M_2 &= \tanh(\eta\, E_2\Phi_2)\\
A &= \text{ReLU}\big(\tanh\big(\eta\big(M_1 M_2^{\top} - M_2 M_1^{\top}\big)\big)\big)\\
\text{idx} &= \text{argtopk}(A[i,:]) \quad \forall i = 1,\dots,n\\
A[i, -\text{idx}] &= 0\,,
\end{aligned} \tag{6}$$

where E_1 and E_2 are randomly initialized learnable node embedding matrices, Φ_1 and Φ_2 are model parameters, η is a hyperparameter controlling the saturation rate of the activation function, and argtopk$(\cdot)$ is a function that returns the index of the top-k largest values of a vector. Unlike GWN, which can be used either standalone or to augment a pre-defined graph, MTGNN learns the graph structure fully end-to-end. These two models are among the first to explore self-learned graph structures. Although other methods have since been proposed, GWN and MTGNN continue to serve as prototypical models for self-learned graph structures.

When the graph structure is learned, some authors introduce a graph regularization term to the training loss function to optimize the learned graph adjacency matrix. This regularization term is typically designed to control the sparsity of the matrix, and to promote graph proximity, encouraging larger entries when the series in the corresponding nodes are "close enough". Some researchers argue that models which generate graphs without prior knowledge may overlook local conditions when constructing adjacency matrices (Huang et al., 2024a). Therefore, it is important to conduct further research in this area to identify the most effective techniques for generating informative graphs. For a more detailed explanation of graph learning models, see He et al. (2024c) and Li et al. (2024f).

Another key aspect in the determination of the graph structure is the choice between using a static or dynamic adjacency matrix, i.e. whether to use the same matrix for all graphs or not. When working with graphs defined in advance by specific metrics, it is common to use either a static matrix or a dynamic matrix generated through a sliding window approach. In contrast, when graphs are learned by the model, dynamic adjacency matrices are typically employed. The use of a dynamic adjacency matrix has the advantage of capturing the dynamic nature of the problem (Han et al., 2024b). However, the learned dynamic graphs often show significant differences between adjacent time steps, whereas real-world graph structures typically evolve smoothly over time. Therefore, this approach may not accurately capture the stable evolution observed in the real world.

Consequently, some researchers are exploring an intermediate approach, assuming that adjacent graph structures follow a basic pattern. Instead of defining static or dynamic adjacency matrices, they fuse a static backbone graph with a dynamic adjacency matrix. The static network captures the common graph structure over time, while the dynamic network focuses on learning the changes over time. An example of this intermediate approach can be found in Mao et al. (2024), which also provides a comparison between this intermediate approach and the classical ones.

In general, there is no rule that can determine in advance the best approach to follow. In fact, it depends on both the application domain and the specific dataset. For this reason, we do not explore this aspect further. As an example, for a detailed discussion of graph construction techniques in traffic flow prediction models, the reader is referred to Fan et al. (2025). Each subsection of the thematic analysis in Section 5 discusses the most prevalent approach for each group of papers.

4.5. Model evaluation

Evaluating the performance of a time series forecasting or classification model is essential to assess its reliability. Moreover, experimental results often show that even when datasets involve the same forecasting task, the transferability of model architectures is limited (Chen et al., 2025). Therefore, a proper evaluation of the model is a crucial aspect. A first key aspect to consider is its accuracy. The accuracy of a model can be measured by many different metrics, which vary between classification and forecasting tasks. Each metric provides its own insight into different aspects of prediction quality, so multiple metrics are typically used for a more comprehensive evaluation. In addition to presenting a table of the error metrics computed for the entire graph, some authors provide a spatial visualization of these errors across the various nodes, as for example in Yang et al. (2023a).

As for forecasting problems, commonly used evaluation metrics include the mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), root relative squared error (RRSE), the coefficient of determination (R^2), and the correlation coefficient (CORR). Let N denote the number of observations, y_i the true value associated with observation i, $\hat{y}_i$ the corresponding output of the model, and the bar denote the average. The formulas for these metrics (for a single-step forecasting horizon) are provided in Table 5.

Similar formulas can be applied to multi-horizon forecasting problems. All the metrics listed, except for the last one, are considered better when their values are lower, as they indicate smaller discrepancies between the predicted and actual values. In contrast, CORR quantifies the linear correlation between actual values and forecasts, and a high correlation is preferable.

As for classification problems, common evaluation metrics include accuracy, precision, recall, and F1 score. Given TP, TN, FP, and FN the number of true positives, true negatives, false positives, and false negatives, respectively, the formulas for the binary classification problem are reported in Table 6. Similar formulas can be applied for the multi-class classification problem.

Besides accuracy, another important aspect to consider is the complexity of the model. Finding an optimal balance between accuracy and complexity is crucial for developing models that are not only accurate but also efficient. For this reason, some authors include the training and inference computational times, as well as the number of parameters of their models, allowing for a comparison of these aspects across differ-

Table 5
Evaluation metrics for single-horizon forecasting tasks and their formulas.

Metrics	Formula
Mean absolute error (MAE)	$\frac{1}{N}\sum_{i=1}^{N}\lvert y_i-\hat{y}_i\rvert$
Mean squared error (MSE)	$\frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2$
Root mean squared error (RMSE)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}$
Mean absolute percentage error (MAPE)	$\frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{y_i-\hat{y}_i}{y_i}\right\rvert\cdot 100$
Root relative squared error (RRSE)	$\sqrt{\frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{N}(y_i-\bar{y})^2}}$
Coefficient of determination (R^2)	$1-\frac{\sum_{i=1}^{N}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{N}(y_i-\bar{y})^2}$
Correlation coefficient (CORR)	$\frac{\sum_{i=1}^{N}(y_i-\bar{y})(\hat{y}_i-\bar{\hat{y}})}{\sqrt{\sum_{i=1}^{N}(y_i-\bar{y})^2\sum_{i=1}^{N}(\hat{y}_i-\bar{\hat{y}})^2}}$

Table 6
Evaluation metrics for binary classification tasks and their formulas.

Metrics	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
F1 score	$\frac{2\cdot\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$

ent models. However, not all authors do so, and even if they do it, the characteristics of the hardware and other settings used by each author must be taken into account when comparing computational times. Consequently, it was not possible to provide an accurate and detailed comparison of the relationship between complexity and performance across the different models in this review. Although creating a plot to compare accuracy and computational times of the different models would be very useful (as in Hong et al., 2025 and Fang et al., 2023a), it is not possible to provide such a comparison here. The authors of the various papers should be encouraged to incorporate such comparisons in their work.

5. Thematic analysis

This section explores the applications of the collected GNN models across different thematic groups. The goal is to provide an overview of available empirical studies, the most common approaches, and the results obtained concerning the discussed themes.

In each following subsection, one per theme, a list of the benchmark models that appear in the selected papers will be provided. Within each theme, they will be classified as: mathematical and statistical models coming from Econometrics, non-GNN machine learning models, and GNN-based models. Mathematical and statistical models are characterized by the fact that they generate forecasts by analyzing a limited amount of data, and they usually struggle with cross-sectional large-scale and temporal long-term dependencies. Non-GNN machine learning models use more complex and highly nonlinear architectures, mainly neural networks, but they are not necessarily able to capture intricate spatio-temporal dependencies within the data. GNN-based models, conversely, attempt to represent these complex dependencies using various techniques, resulting in better, though not perfect, accuracy. In addition, information on the most common datasets will be given, along with the best results reported in the literature. All results presented in the tables of this SLR are taken directly from the tables of the selected papers, as we did not conduct any further experiments to obtain additional results. When examining the results tables, the reader is invited to consult the GitHub repository associated with this review, which provides interactive functionality for sorting and filtering models by any metric and generating plots, making it easy to analyze and compare the results. Note that in the tables which list benchmark models we have included references to any GNN model found. In the results tables, instead, we have explicitly referenced only those models proposed in the selected papers, in order to highlight them. Further information about the models used as benchmarks can be found either in the benchmark tables or in the papers where they are used as benchmarks. The most common benchmarks used across all groups of papers are also listed in the GitHub repository.

The thematic groups of papers are presented in alphabetical order, with the exception of the "Generic" applications group (which cannot be directly attributed to a specific case study) and the "Other topics" group (focusing on specific problems of other disciplines). In subsections with a large number of papers and high homogeneity of the datasets, more precise comparisons of the results and in-depth analyses will be conducted.

5.1. Energy

The first thematic group is "Energy" (with 33 out of 366 papers), which includes all the studies related to energy systems. In particular, it includes research on electricity load, energy consumption, and power generation forecasting. These topics are somehow connected to those of the "Environment" subsection discussed later (Subsection 5.2). For example, green energy sources are associated with environmental phenomena such as wind speed and solar radiation inflow. Our rationale for this selection is that here we focus on energy applications, whereas Subsection 5.2 will refer to the study of environmental data that may or may not be related to energy applications. Wind speed forecasting, for instance, is connected to wind power generation due to the cubic relationship between wind speed and wind power (Bentsen et al., 2023a). However, wind speed forecasting may also be of interest for other reasons, and thus it is included in the more general Subsection 5.2.

5.1.1. Overview

Energy forecasting is crucial for electricity power grid stability and operational efficiency. Accurate load and generation forecasts ensure that supply meets real-time demand, preventing outages and instability, and maintaining a reliable supply of power. In addition, effective forecasting allows for optimal scheduling of power plants and energy resources, reducing operational costs and improving overall system efficiency. In the papers within this theme, the majority of econometric and non-GNN machine learning models tend to focus on time series from a single site or consider multiple sites without explicitly capturing the relationships between them. GNN models may be an innovative and effective approach to addressing energy related problems.

An overview of the selected papers reveals a relevant interest in the application of GNNs in the energy field starting from 2022. The most frequently studied fields include forecasting of wind (He et al., 2022a; Li, 2022; Yang et al., 2024a; Yi et al., 2024; Yu et al., 2020) and solar power (Qin et al., 2023; Simeunović et al., 2022a,b; Verdone et al., 2024), which are renewable energy sources characterized by their intermittency. The most popular journal among the selected papers is *Applied Energy* by Elsevier, with 5 published papers, and the only "Energy" conference paper was presented at IJCAI.

5.1.2. Datasets

The study of the selected papers in the "Energy" group suggests that there are no particularly common or widely recognized benchmark datasets within this field. Indeed, researchers often focus on specific datasets, typically collected within the university campus or in the country where they are located. For the same reason, the links to these

Table 7
List of public datasets in the "Energy" group and their corresponding links.

Dataset	Used in	Link
Commercial and residential load	(Feng et al., 2024b)	https://www.osti.gov/biblio/1788456
Danish smart heat meters	(Wang et al., 2023k)	https://doi.org/10.5281/zenodo.6563114
IEEE bus systems	(Zhao et al., 2022b)	https://doi.org/10.1109/UPEC.2015.7339813 (source paper)
Individual household electric power consumption	(Huang et al., 2024b)	https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption
JERICHO-E-usage	(Wang et al., 2023k)	https://doi.org/10.6084/m9.figshare.c.5245457.v1
NREL	(He et al., 2022a), (Simeunović et al., 2022b) and (Yu et al., 2020)	https://www.nrel.gov/
OpenEI residential load	(Seol et al., 2024)	https://openei.org/datasets/files/961/pub/RESIDENTIAL_LOAD_DATA_E_PLUS_OUTPUT/HIGH/
OPSD	(Zhang et al., 2023d)	https://open-power-system-data.org/
PJM hourly energy consumption	(Qiu et al., 2024)	https://www.pjm.com/markets-and-operations/data-dictionary
PVGIS	(Verdone et al., 2024)	http://re.jrc.ec.europa.eu/pvgis/apps4/pvest.php
PV Switzerland	(Simeunović et al., 2022a) and (Simeunović et al., 2022b)	https://doi.org/10.1109/IJCNN48605.2020.9207573 (source paper)
Residential heat and electricity demand	(Miraki et al., 2024)	https://ieee-dataport.org/open-access/8-years-hourly-heat-and-\protect\penalty-\@Melectricity-demand-residential-building
SGCC dataset	(Ida Evangeline et al., 2024)	http://www.sgcc.com.cn/
Southern power grid	(Huang et al., 2024b)	https://www.csg.cn/
UMass smart*	(Wang et al., 2023h)	https://traces.cs.umass.edu/docs/traces/smartstar/

datasets are not always available. In Table 7 are listed the links to the public datasets mentioned in the papers.

Three of the selected papers (He et al., 2022a; Simeunović et al., 2022b; Yu et al., 2020) use data from the National Renewable Energy Laboratory (NREL), a national laboratory of the U.S. Department of Energy (https://www.nrel.gov/). The data time granularity ranges from 1 minute to 1 day, and the forecasting horizon from tens of minutes to days. These quantities depend on the dataset, the domain of application, and the purpose of the forecast. Most datasets require pre-processing, including missing data interpolation, normalization, and satellite image processing.

5.1.3. Types of models

As for the taxonomy of the proposed GNN models, 17 out of 33 papers use a convolutional GNN, and 8 use an attentional GNN. Seven papers use both convolutional and attentional approaches, and one paper (Giamarelos & Zois, 2024) uses the original recurrent approach on a graph defined via the visibility algorithm. As to the graph structure used, the papers typically provide only a brief description. For example, only few papers highlight whether the graph structure is static or dynamic, and the way in which it is constructed is often described summarily. In some papers, the graph structure reflects the geographic location of the elements (e.g., wind or solar power plants, as in Qin et al., 2023; Verdone et al., 2024; Yu et al., 2020), whereas in others it is based on the correlation or similarity between time series (as in Rawal & Ahmad, 2024a). In some studies, a pre-defined structure is imposed and the weighted adjacency matrix is learned directly from the model, often using the attention mechanism as in Simeunović et al. (2022b). The majority of papers in this group rely on a static graph.

The most common loss function used to train these models is the MSE. Many papers mention the use of the programming languages Python and Matlab, and few of them mention the use of the Python libraries TensorFlow (Abadi et al., 2015), PyTorch (Paszke et al., 2019), and PyTorch Geometric (Fey & Lenssen, 2019) for the implementation of the GNN model. In this group, only Wang et al. (2023h) provide the link to the source code of the proposed residential load forecasting with multiple correlation temporal graph neural networks (RLF-MGNN) model (available at https://codeocean.com/capsule/9294192/tree/v1).

5.1.4. Benchmark models

Table 8 lists the benchmark models used in the "Energy" group by at least two papers included in this review.

The majority of the papers only use non-GNN machine learning benchmarks. Some papers use simple mathematical and statistical models, such as the ARIMA model and the historical average. Only few papers use GNN-based models as benchmarks, and the most popular benchmark among them is the spatio-temporal graph convolutional network (STGCN). Before 2024, the only benchmark used by two papers was the spatio-temporal autoregressive model (ST-AR). This is due to the fact that this thematic field has not been extensively explored in the past, and only a very limited number of GNN models have been specifically developed for energy forecasting.

5.1.5. Results

In general, the authors of the papers in this group claim that their proposed GNN model outperforms the benchmarks. However, in some cases, it turns out that basic statistical methods may achieve good results as well (Qiu et al., 2024). The most common error metrics used are the MAE, the RMSE, and the Normalized Root mean squared Error (NRMSE). Some papers calculate these error metrics across different seasons to evaluate the model's performance under different conditions. An example is provided in Verdone et al. (2024), where the authors also use the GNNExplainer (Ying et al., 2019) to assess the influence of different variables.

It is not possible to compare the accuracy of the models included in this group, because no common benchmark datasets were used. The only two papers that study the same dataset are written by the same authors (Simeunović et al., 2022a,b), and their most recent paper includes a comparison with the models proposed in the first one.

5.2. Environment

The thematic group "Environment" includes a relevant number of selected papers (43 out of 366). This suggests a considerable research interest on the application of GNNs in this field. However, this group is highly fragmented, as it includes a large number of subdomains and applications, all related to the study of environmental data.

5.2.1. Overview

The group of papers related to environmental topics is broad, and includes papers on disciplines such as physics, climatology, oceanography, and atmospheric science. The breadth of the group is reflected in the number of case studies, which cover air quality prediction (in terms of $PM_{2.5}$ concentration), sea temperature, wind speed, and other applications. Forecasting these quantities can be useful for several reasons. For instance, predicting wind speed or rainfall can assist in anticipating some extreme weather phenomena, and is also related to the prediction of green energy outputs. For example, Bentsen et al. (2023a,b) estimate

Table 8
List of benchmark models in the "Energy" group divided per category.

Category	Model	Used in
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	(Wang et al., 2023k), (Zhang et al., 2023d), (Simeunović et al., 2022b), (Hu et al., 2022), (Yi et al., 2024), (Rawal & Ahmad, 2024a), (Giamarelos & Zois, 2024), (Miraki et al., 2024), (Rawal & Ahmad, 2024b), (Verdone et al., 2024) and (Lin & Wu, 2021)
	Historical average (HA)	(Zhang et al., 2023h) and (Qiu et al., 2024)
	Vector ARIMA	(Yang et al., 2024a), (Yi et al., 2024), (Rawal & Ahmad, 2024b), (Zhang et al., 2023h) and (Qiu et al., 2024)
Non-GNN machine learning methods	Autoformer (Wu et al., 2021)	(Yi et al., 2024) and (Miraki et al., 2024)
	Bidirectional long-short term memory network (BiLSTM) (Graves & Schmidhuber, 2005)	(Wang et al., 2023k) and (Zhang et al., 2024b)
	Convolutional neural network (CNN)	(Wang et al., 2023k), (Ganjouri et al., 2023), (Simeunović et al., 2022a), (Simeunović et al., 2022b), (Rawal & Ahmad, 2024b) and (Cai et al., 2024)
	Hybrid convolutional neural network and long-short term memory network (CNN-LSTM)	(Wang et al., 2023k), (Wang et al., 2023h) and (Pu et al., 2024)
	Encoder-decoder architectures (ED)	(Wang et al., 2023k), (Simeunović et al., 2022a) and (Simeunović et al., 2022b)
	Feed-forward neural network (FNN)	(Wang et al., 2023k), (Ganjouri et al., 2023), (Hu et al., 2022), (Li, 2022), (Pu et al., 2024) and (Lin & Wu, 2021)
	Gated recurrent unit (GRU)	(Wang et al., 2023k), (Hu et al., 2022), (Zou et al., 2024b), (Giamarelos & Zois, 2024), (Rawal & Ahmad, 2024b) and (Cai et al., 2024)
	Informer (Zhou et al., 2021)	(Wang et al., 2023k) and (Zhang et al., 2023d)
	k-nearest neighbors (KNN)	(Ganjouri et al., 2023), (Yu et al., 2020), (Ida Evangeline et al., 2024) and (Rawal & Ahmad, 2024b)
	Long-short term memory network (LSTM)	(Wang et al., 2023k), (Zhang et al., 2023d), (He et al., 2022a), (Zhao et al., 2022b), (Yu et al., 2020), (Yi et al., 2024), (Zou et al., 2024b), (Hu et al., 2024c), (Liu et al., 2024b), (Miraki et al., 2024), (Rawal & Ahmad, 2024b), (Huang et al., 2024b), (Cai et al., 2024), (Feng et al., 2024b), (Verdone et al., 2024), (Yu et al., 2024c) and (Lin & Wu, 2021)
	Long-short term time series network (LSTNet) (Lai et al., 2018)	(Wang et al., 2023k), (Yang et al., 2024a) and (Zou et al., 2024b)
	Recurrent neural network (RNN)	(Zhang et al., 2023d), (Wang et al., 2023h) and (He et al., 2022a)
	Seq2Seq (Sutskever et al., 2014)	(Hu et al., 2024c) and (Rawal & Ahmad, 2024b)
	Support vector regression (SVR)	(Simeunović et al., 2022a), (Simeunović et al., 2022b), (Yu et al., 2020), (Li, 2022), (Giamarelos & Zois, 2024), (Ida Evangeline et al., 2024), (Rawal & Ahmad, 2024b), (Huang et al., 2024b), (Feng et al., 2024b) and (Lin & Wu, 2021)
	Transformer (Vaswani et al., 2017)	(Zhang et al., 2023d), (Hu et al., 2024c) and (Rawal & Ahmad, 2024b)
	Extreme gradient boosting (XGBoost)	(Hu et al., 2022), (Zou et al., 2024b), (Hu et al., 2024c) and (Miraki et al., 2024)
GNN methods	Diffusion convolutional recurrent neural network (DCRNN) (Li et al., 2018)	(Verdone et al., 2024), (Zhang et al., 2023h) and (Qiu et al., 2024)
	Multivariate time series forecasting with graph neural network (MTGNN) (Wu et al., 2020c)	(Yang et al., 2024a), (Liu et al., 2024b) and (Miraki et al., 2024)
	Spatio-temporal autoregressive model (STAR) (Carrillo et al., 2020)	(Simeunović et al., 2022a) and (Simeunović et al., 2022b)
	Spatio-temporal graph convolutional network (STGCN) (Yu et al., 2018)	(Zhang et al., 2024b), (Miraki et al., 2024), (Feng et al., 2024b), (Pu et al., 2024) and (Yu et al., 2024c)

the wind power forecasting error obtained by using wind speed forecasting models. As another example, predicting sea surface temperature can be useful for weather forecasting, fishing directions, and disaster warnings (Yang et al., 2023a). Moreover, monitoring and forecasting environmental data are crucial for evaluating the impact of human activities on the environment and tracking the progression of climate change.

The methods for forecasting environmental data are typically categorized as numerical methods, statistical methods, and machine learning methods. Numerical methods are based on atmospheric models, and are designed to quantify the interaction of different atmospheric variables. The accuracy of these models depends on the availability of data, and the mathematical simulations needed to get the forecasts may take days or even weeks, thus limiting the ability to make good short-term forecasts. Linear statistical methods leverage long-term dependencies in the recorded data by using regression-like models. However, they cannot capture non-linear relationships in the dataset, which limits their power. Machine learning methods, on the other hand, are often advanced generalizations of linear statistical methods that can capture more complex and non-linear relationships in the data.

An overview of the selected papers reveals that there has been a rapid increase in interest on this theme among the GNN research community too, and more than 35 of the selected papers were published from 2023. The most investigated data are related to sea temperature (Chen et al., 2022b; Gao et al., 2023b; Kim et al., 2023b; Pan et al., 2023; Sheng et al., 2023; Sun et al., 2021; Wang et al., 2022b; Yang et al., 2023a), wind speed (Bentsen et al., 2023a,b; Dong et al., 2023; Gao et al., 2023a; Geng et al., 2021; Liu et al., 2024c; Ren et al., 2023), and $PM_{2.5}$ concentration forecasting (Kim et al., 2023a; Li et al., 2023f; Liao et al., 2024a; Liu & Li, 2023; Ni et al., 2023; Pei et al., 2022; Ren et al., 2024; Su et al., 2023; Xia et al., 2024). Almost every selected paper is published in a different journal, with the exception of *Energy*, *Engineering Applications of Artificial Intelligence*, *Journal of Cleaner Production*, *Knowledge-Based Systems*, *Science of the Total Environment* by Elsevier, each with two published papers. As for conference papers, the three "Environment" papers were presented at KDD, IJCAI and CIKM.

5.2.2. Datasets

The analysis of the selected papers shows that in this thematic group there is no standardized benchmark dataset. The publicly available datasets cited in the papers are listed in Table 9.

Six of the selected papers (Dong et al., 2023; Gao et al., 2023b; Seol et al., 2024; Sheng et al., 2023; Wang et al., 2022b; Yang et al.,

Table 9
List of public datasets in the "Environment" group and their corresponding links.

Dataset	Used in	Link
AgroData-10	(Yang et al., 2023a)	https://www.aoml.noaa.gov/phod/argo
Carbon monitor	(Gong et al., 2024)	https://carbonmonitor.org/
CCMP wind data	(Ren et al., 2023), (Geng et al., 2021) and (Gao et al., 2023a)	http://data.remss.com
China environmental monitoring station PM2.5	(Liu & Li, 2023), (Pei et al., 2022) and (Xia et al., 2024)	https://www.cnemc.cn/
China national urban air quality	(Chen et al., 2023d) and (Ding & Noh, 2023)	https://github.com/Friger/GAGNN
Copernicus 3D thermohaline data	(Pan et al., 2023)	https://resources.marine.copernicus.eu/products
Delaware river basin	(Chen et al., 2022b)	https://waterdata.usgs.gov/nwis
ECMWF east China sea	(Peng et al., 2023)	https://github.com/Boltzxuann/GIPMN/tree/dataset
ECMWF south and east China sea	(Zhang et al., 2023i)	http://apps.ecmwf.int/datasets/data/interim-full-daily†
HadCRUT5	(Wang et al., 2024l)	https://crudata.uea.ac.uk/cru/data/temperature/
HUC12	(Azmat et al., 2023)	https://hawqs.tamu.edu/
Jinan PM2.5	(Liao et al., 2024a)	https://github.com/liaohaibing/MGST_GNN/tree/master
KnowAir	(Ni et al., 2023)	https://github.com/shuowang-ai/PM2.5-GNN
Korean peninsula sea data	(Kim et al., 2023b)	https://www.nifs.go.kr/risa/main.risa
NARR weather conditions	(He et al., 2024a)	https://psl.noaa.gov/data/gridded/data.narr.html
NOAA sea datasets	(Yang et al., 2023a), (Gao et al., 2023b), (Wang et al., 2022b), (Dong et al., 2023), (Sheng et al., 2023) and (Seol et al., 2024)	https://www.ndbc.noaa.gov/
Norwegian offshore wind	(Bentsen et al., 2023a) and (Bentsen et al., 2023b)	https://frost.met.no/index.html
Overbetuwe groundwater data	(Taccari et al., 2024)	https://github.com/mlttac/GroundwaterFlowGNN
Taiwan air quality dataset	(Su et al., 2023)	https://data.gov.tw/en
UrbanAir	(Ni et al., 2023)	https://doi.org/10.1016/j.chemosphere.2018.12.128 (source paper)
US EPA $PM_{2.5}$	(Chen et al., 2023d) and (Li et al., 2023f)	https://aqs.epa.gov/aqsweb/airdata/download_files.html
WeatherBench	(He et al., 2024a)	https://github.com/pangeo-data/WeatherBench
Yangtze river PM2.5	(Liao et al., 2024a)	https://github.com/liaohaibing/MGST_GNN/tree/master

2023a) use National Oceanic and Atmospheric Administration (NOAA) sea datasets (https://www.noaa.gov/) from the U.S. Department of Commerce (US DOC). The US DOC website permits users to download daily, weekly and monthly mean optimum interpolation sea surface temperature (OISST) data from September 1981 for many geographical locations. In over half of the papers, exogenous variables are incorporated into the model. These include weather data (e.g., humidity, rainfall, pressure, temperature, wind) and, in the case of $PM_{2.5}$ concentration forecasting, concentration of pollutants (like CO, NO_2, O_3, PM_{10} and SO_2).

Overall, many papers also consider exogenous variables, in particular weather data, as they have the greatest influence on environmental data.

The data time granularity ranges from 1 minute to 1 month, depending on the case study, and the forecasting horizon ranges from 10 minutes to more than one year. Most datasets require some type of preprocessing, including interpolation of missing data, removal of outliers and normalization.

5.2.3. Types of models

Regarding the taxonomy of the proposed GNN models, the majority of papers present convolutional GNNs (28 out of 43 papers), followed by 8 attentional GNNs, and by 3 hybrid architectures. The description in 4 of the papers (Chen et al., 2022b; Ding & Noh, 2023; Liao et al., 2024a; Ren et al., 2024), however, does not allow us to specify the classification of the model within the proposed taxonomy. As for the graph structure, not all of the papers describe it with sufficient precision, and some of them are vague about the graph construction and its static or dynamic nature. In almost half of the papers, the edge weights are learned directly from the model, often using the graph attention mechanism. When the graph structure is defined manually, the most popular criterion used is the spatial distance between the sites (d), even in its exponential (e^{-d}) or inverse proportion ($1/d$) formulation, or similarity measures, such as cosine similarity and correlation of the time series. Finally, there are a few papers where more than one graph structure is fused together in order to capture more complex dynamics, as in Liu and Li (2023). Almost all the papers in this thematic group deal with multivariate time series, with the exception of Wang et al. (2024l), which studies a univariate time series of global average temperature. In this work, the authors treat each time step t as a node v_t in the graph, and the adjacency matrix is constructed in such a way that v_t is influenced by v_{t-1} and v_{t+1}.

Not all papers openly write down the loss function used to train the models. Among those that do, the most popular loss functions are MSE and MAE. Many papers mention the use of the programming language Python and of the library PyTorch for the implementation of the models. Few papers also provide a link to the source code for the proposed model, as shown in Table 10.

5.2.4. Benchmark models

Table 11 presents the benchmark models employed in the "Environment" group by at least two articles examined in this review.

The majority of the benchmarks used in this thematic group fall within the category of non-GNN machine learning methods, although there are several GNN benchmarks as well. The two most common benchmark models are LSTMs and GRUs. These models are widely used by environmental data forecasters due to their ability to capture temporal dependencies, and are considered a reliable benchmark in the field. As for GNN models, the most common benchmarks are the graph convolutional neural network and long-short term memory network (GC-LSTM) (Qi et al., 2019) (which appears only in quality air forecasting problems), and the spatio-temporal graph convolutional network (STGCN) (Yu et al., 2018). The GC-LSTM network is a model that integrates graph convolutional networks and long-short-term memory networks, proposed to forecast the spatio-temporal variation of $PM_{2.5}$ concentration. In the original paper, the GC-LSTM model works with a predefined graph based on the geographical distance between air quality stations. The input layer of the GC-LSTM model receives historical air quality observations, meteorological variables, spatial predictors, and temporal predictors. This information is processed through a graph convolution operation to extract spatial features. After that, the temporal feature extraction is performed using a LSTM network, which takes as input the graph convolutional features concatenated with the original signals. The STGCN model, on its part, was proposed in the traffic domain and works with pre-defined adjacency matrices computed based on the distances among stations in the traffic network. The STGCN model is composed of two spatio-temporal convolutional blocks and a fully-connected output layer. Each convolutional block contains two temporal gated convolution layers and one spatial graph convolu-

Table 10
List of source codes of the "Environment" models in the review.

Model	Link
Domain inspired temporal graph convolution neural network (Azmat et al., 2023)	https://github.com/IBM/tgcn-soil-moisture
Dynamic spatial-temporal graph convolutional recurrent network (DSTGCRN) (Gong et al., 2024)	https://github.com/PalaceTony/DSTGCRN
Dynamic spatiotemporal graph neural network (DST-GNN) (Liao et al., 2024a)	https://github.com/liaohaibing/MGST_GNN/tree/master
Group-aware graph neural network (GAGNN) (Chen et al., 2023d)	https://github.com/Friger/GAGNN
Gridded information propagation and mixing network (GIPMN) (Peng et al., 2023)	https://github.com/Boltzxuann/GIPMN/tree/dataset
GroundwaterFlowGNN (Taccari et al., 2024)	https://github.com/mlttac/GroundwaterFlowGNN
Hierarchical graph recurrent network (HiGRN) (Yang et al., 2023a)	https://github.com/Neoyanghc/HiGRN
Physics-aware graph networks (PaGN) (Seol et al., 2024)	https://github.com/eunviho/novel_pagn
Spatio-temporal FFTransformer (ST-FFTransformer) (Bentsen et al., 2023a)	https://github.com/LarsBentsen/FFTransformer

tion layer in the middle. The code for the STGCN model is available at https://github.com/VeritasYin/STGCN_IJCAI-18. Finally, it is important to point out that the so-called multivariate time series forecasting with graph neural network (MTGNN) model proposed by Wu et al. (2020c) is often reported in the papers using it as the second-best performing model, thus it probably deserves special attention and further investigation in future research.

5.2.5. Results

In each paper of this group, it is stated that the proposed model is significantly better than the benchmarks. The accuracy of the models is measured in terms of MAE, RMSE, and MAPE. Among the papers, there is a high diversity in the choice of the proposed datasets. However, there are two sets of papers using the same dataset, whose results are compared hereafter.

The first dataset is the CCMP wind speed dataset (available at http://data.remss.com), which contains 3,942 geographical grid points from the east and southeast sea areas of China. The three papers using it (Gao et al., 2023a; Geng et al., 2021; Ren et al., 2023) select 120 points from the area and use data records from January 2010 to April 2019 at 6 hours intervals, with a total of 13,624 samples at each node, for 10 different forecasting horizons. All papers present results for the complete set of 120 nodes and a subset of nodes. Since these results are similar, only the average results for all the 120 nodes are reported in Table 12 for the sake of simplicity.

For all the time horizons considered in the papers, the dynamic adaptive spatio-temporal graph neural network (DASTGN) model proposed by Gao et al. (2023a) has the highest accuracy. The DASTGN model is composed of a graph generation module and a spatio-temporal convolution module. The dynamic adaptive graph generation module generates a static graph to model long-term stable dependencies, and a dynamic graph to model the short-term dynamics. These graphs are then merged into an optimal dynamic graph. The spatio-temporal convolution module consists of an input module, a stack of spatio-temporal layers connected with residual and skip connections, and an output module that generates wind speed forecasts. Other two well performing models are the data-based adaptive graph learning network (DAGLN) (Ren et al., 2023), and the multivariate time series forecasting with graph neural network (MTGNN) (Wu et al., 2020c). The DAGLN model was proposed by Ren at al. in 2023, and uses an encoder-decodes architecture. The encoder includes an adaptive graph learning module that learns the optimal adjacency matrix starting from a pre-defined one obtained by using the DTW algorithm, a graph convolution with node adaptive parameter learning algorithm for personalized learning of parameter space, and a GRU for temporal modeling. Then, this information is fed into the decoder that operates a convolutional and a linear operation to produce the wind speed forecast. The MTGNN model is a well-known state-of-the-art model for multivariate time series forecasting, here included in the "Generic" group of papers. It incorporates a graph learning layer that learns a graph adjacency matrix from scratch, followed by a stack of graph convolution and temporal convolution modules to capture spatial and temporal dependencies, and an output module. To avoid the problem of vanishing gradients, residual and skip connections are added between spatial and temporal convolutional modules.

The second dataset shared by two papers (Chen et al., 2023d; Ding & Noh, 2023) is called China National Urban Air Quality dataset (available at https://github.com/Friger/GAGNN). It contains air quality index data (AQI) of 209 cities, collected from January 2017 to April 2019 at 1 h granularity, for a total of 20,370 samples. Both these papers integrate exogenous weather variables (humidity, wind direction, wind speed, rainfall, air pressure, temperature, and visibility) collected from Envicloud (http://www.envicloud.cn/). The average accuracy of the models used in the two papers is compared in Table 13.

As from Table 13, the hybrid interpretable neural network and graph neural network model (INNGNN) (Ding & Noh, 2023) is the most accurate model for all time horizons except the 1 h horizon, where it is beaten by the meta-graph convolutional recurrent network model (MegaCRN) (Jiang et al., 2023b). The authors attribute this result to the fact that in the short term the AQI is strongly influenced by nearby cities, whereas the MegaCRN model is more focused on local features. The INNGNN model consists of a temporal and a spatial dependency module. The temporal module employs self-attention and interpretable neural networks (INN) to extract local and global features of time series data, effectively identifying periodicity and trend of the AQI time series. After that, the spatial module has an encoder-decoder architecture where GNN modules extract spatial dependencies across geographic locations, represented by an adjacency matrix based on spatial distance. The MegaCRN model, introduced for traffic forecasting, includes a meta-graph learner module and an encoder-decoder spatial module built using a series of convolutional GNNs. The source code for the MegaCRN model can be accessed at https://github.com/deepkashiwa20/MegaCRN.

5.3. Finance

"Finance" is another emerging theme of study, though not yet widely explored, with just 14 out of 366 selected papers. The difficulty of predicting financial data is a well-established fact. This is due to the inherently complex nature of markets, the influence of geopolitical events on them, and the unpredictable behavior of humans which is often irrational and difficult to predict. This complexity makes financial time series highly volatile, and accurate forecasts and data modeling are essential to develop effective trading strategies. Spatio-temporal GNNs are taken into consideration to model the inter-dependencies between variables together with series dynamics.

5.3.1. Overview

The "Finance" thematic group is relatively narrow in terms of subthemes. This is in part due to the limited number of published papers. Half of the studies are concentrated on stock price forecasting (Chen et al., 2024b; Huang et al., 2022; Pang et al., 2023; Sun et al., 2023; Tian et al., 2023; Wang et al., 2023f; Xiang et al., 2022), with the aim of forecasting the future trend of the price of a company. Sometimes the stock prediction problem is seen as a classification task. This is because, due to the stochastic nature and volatility of financial markets, predicting just the direction of price movements ("up", "neutral", "down") can

Table 11
List of benchmark models in the "Environment" group divided per category.

Category	Model	Used in
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	(Yang et al., 2023a), (Kim et al., 2023b), (Bentsen et al., 2023b), (Lira et al., 2022), (Wu & Kang, 2024), (Wang et al., 2024l), (Xia et al., 2024) and (He et al., 2024a)
	Historical average (HA)	(Su et al., 2023), (Ni et al., 2023), (Yang et al., 2023a), (Lira et al., 2022) and (He et al., 2024a)
	Naive	(Bentsen et al., 2023a), (Bentsen et al., 2023b) and (Liu et al., 2024c)
	Vector autoregression (VAR)	(Yang et al., 2023a), (Bentsen et al., 2023b), (Lira et al., 2022) and (Gong et al., 2024)
Non-GNN machine learning methods	Bidirectional long-short term memory network (BiLSTM) (Graves & Schmidhuber, 2005)	(Kim et al., 2023b) and (Dong et al., 2023)
	Combined FC-LSTM and convolution neural network (CFCC-LSTM) (Yang et al., 2018)	(Pan et al., 2023), (Wang et al., 2022b) and (Wang et al., 2024l)
	DLinear (Zeng et al., 2023)	(Ren et al., 2023) and (Wu et al., 2024a)
	Hybrid convolutional neural network and gated recurrent unit (CGRU) (Xu et al., 2019)	(Ren et al., 2023), (Geng et al., 2021) and (Gao et al., 2023a)
	Convolutional neural network (CNN)	(Li et al., 2023a) and (Dong et al., 2023)
	Hybrid convolutional neural network and long-short term memory network (CNN-LSTM)	(Li et al., 2023f), (Sun et al., 2021), (Chen et al., 2024c) and (Xia et al., 2024)
	Convolutional long-short term memory network (ConvLSTM) (Shi et al., 2015)	(Yang et al., 2023a), (Sun et al., 2021) and (Li et al., 2024d)
	Feed-forward neural network (FNN)	(Liu & Li, 2023), (Kim et al., 2023a), (Lira et al., 2022), (Gong et al., 2024), (Seol et al., 2024) and (Wang et al., 2024l)
	Gated recurrent unit encoder–decoder (GED) (Xie et al., 2020a)	(Gao et al., 2023b), (Wang et al., 2022b) and (Sheng et al., 2023)
	Gated recurrent unit (GRU)	(Liu & Li, 2023), (Ni et al., 2023), (Kim et al., 2023a), (Pei et al., 2022), (Lira et al., 2022), (Bai & Tahmasebi, 2022), (Dong et al., 2023), (Ren et al., 2024), (Wu et al., 2024a), (Seol et al., 2024), (Wang et al., 2024l) and (He et al., 2024a)
	Informer (Zhou et al., 2021)	(Li et al., 2023a), (Sheng et al., 2023), (Liao et al., 2024a), (Wu et al., 2024a), (Xia et al., 2024) and (He et al., 2024a)
	Long-short term memory network (LSTM)	(Chen et al., 2023d), (Liu & Li, 2023), (Su et al., 2023), (Li et al., 2023f), (Ding & Noh, 2023), (Ni et al., 2023), (Kim et al., 2023a), (Pei et al., 2022), (Yang et al., 2023a), (Li et al., 2023a), (Zhang et al., 2023i), (Kim et al., 2023b), (Pan et al., 2023), (Gao et al., 2023b), (Lira et al., 2022), (Wang et al., 2022b), (Bai & Tahmasebi, 2022), (Dong et al., 2023), (Sheng et al., 2023), (Kim et al., 2024a), (Ren et al., 2024), (Wu et al., 2024a), (Seol et al., 2024), (Chen et al., 2024c), (Wang et al., 2024l), (Xia et al., 2024), (Bobakov et al., 2024), (Chen et al., 2022b), (Azmat et al., 2023) and (He et al., 2024a)
	Long-short term time series network (LSTNet) (Lai et al., 2018)	(Li et al., 2024d) and (Bobakov et al., 2024)
	Predictive deep convolutional neural network (PDCNN) (Zhu et al., 2018)	(Ren et al., 2023) and (Geng et al., 2021)
	Random forest (RF)	(Ni et al., 2023), (Wu et al., 2024a) and (Wang et al., 2024l)
	Recurrent neural network (RNN)	(Dong et al., 2023) and (Seol et al., 2024)
	Support vector regression (SVR)	(Su et al., 2023), (Ni et al., 2023), (Pan et al., 2023), (Gao et al., 2023b), (Lira et al., 2022), (Gong et al., 2024), (Wang et al., 2024l) and (Xia et al., 2024)
	Temporal convolutional network (TCN) (Bai et al., 2018)	(Ni et al., 2023), (Li et al., 2023a), (Li et al., 2024d), (Chen et al., 2024c), (Xia et al., 2024) and (Bobakov et al., 2024)
	Temporal pattern attention long-short term memory network (TPA-LSTM) (Shih et al., 2019)	(Ni et al., 2023), (Ren et al., 2023), (Zhang et al., 2023i), (Pan et al., 2023), (Geng et al., 2021) and (Gao et al., 2023a)
	Transformer (Vaswani et al., 2017)	(Li et al., 2023a) and (Kim et al., 2023b)
	Hybrid wavelet random forest and deep belief network (Wavelet-DBN-RF) (Jiajun et al., 2020)	(Ren et al., 2023), (Geng et al., 2021) and (Gao et al., 2023a)
	Extreme gradient boosting (XGBoost)	(Chen et al., 2023d), (Liu & Li, 2023), (Ding & Noh, 2023), (Dong et al., 2023) and (Wu et al., 2024a)
GNN methods	Adaptive graph convolutional recurrent network (AGCRN) (Bai et al., 2020)	(Ni et al., 2023), (Gong et al., 2024), (Seol et al., 2024) and (Chen et al., 2024c)
	Attention-based spatial-temporal graph convolutional network (ASTGCN) (Guo et al., 2019)	(Wu & Kang, 2024), (Chen et al., 2024c) and (He et al., 2024a)
	Diffusion convolutional recurrent neural network (DCRNN) (Li et al., 2018)	(Wu & Kang, 2024) and (He et al., 2024a)
	Graph convolutional neural network and long-short term memory (GC-LSTM) (Qi et al., 2019)	(Chen et al., 2023d), (Liu & Li, 2023), (Ding & Noh, 2023), (Ni et al., 2023), (Kim et al., 2023a), (Liao et al., 2024a) and (Ren et al., 2024)
	Graph convolutional network (GCN)	(Lira et al., 2022), (Sun et al., 2021) and (Kim et al., 2024a)
	Graph WaveNet (GWN) (Wu et al., 2019)	(Chen et al., 2023d), (Ni et al., 2023), (Gao et al., 2023a), (Sheng et al., 2023), (Wu & Kang, 2024) and (Chen et al., 2024c)

Table 11
Continued

Hierarchical graph convolution network (HGCN) (Guo et al., 2021)	(Chen et al., 2023d) and (Yang et al., 2023a)
Multivariate time series forecasting with graph neural network (MTGNN) (Wu et al., 2020c)	(Ni et al., 2023), (Zhang et al., 2023i), (Gao et al., 2023a), (Li et al., 2024d), (Gong et al., 2024), (Bobakov et al., 2024) and (He et al., 2024a)
Multi long-short term memory network (Multi-LSTM) (Ghaderi et al., 2017)	(Ren et al., 2023), (Geng et al., 2021) and (Gao et al., 2023a)
Superposition graph neural network (SGNN) (Yu et al., 2020)	(Ren et al., 2023) and (Geng et al., 2021)
Spatio-temporal graph convolutional network (STGCN) (Yu et al., 2018)	(Su et al., 2023), (Ni et al., 2023), (Yang et al., 2023a), (Pan et al., 2023), (Sheng et al., 2023), (Wu & Kang, 2024), (Chen et al., 2024c), (Xia et al., 2024) and (He et al., 2024a)
Spatio-temporal correlation graph neural network (STGN) (Geng et al., 2021)	(Ren et al., 2023) and (Gao et al., 2023a)
Spatio-temporal synchronous graph convolutional network (STSGCN) (Song et al., 2020a)	(Chen et al., 2024c) and (Xia et al., 2024)
Temporal graph convolutional network (T-GCN) (Zhao et al., 2020b)	(Ni et al., 2023), (Li et al., 2023a), (Pan et al., 2023), (Azmat et al., 2023) and (He et al., 2024a)

Table 12
Comparison of the average accuracy of the different models on the CCMP wind speed dataset for different time horizons, expressed in terms of MAE and RMSE. The smallest errors are underlined. Numbers from the original papers.

Model	Metrics	6 h	12 h	18 h	1 d	2 d	3 d	4 d	5 d	6 d	7 d
CGRU	MAE	1.658	1.795	1.937	2.038	2.290	2.401	2.478	2.525	2.556	2.594
	RMSE	2.100	2.277	2.461	2.594	2.911	3.042	3.141	3.198	3.245	3.285
DAGLN (Ren et al., 2023)	MAE	1.068	1.219	1.346	1.443	1.716	1.852	1.935	1.984	2.019	2.067
	RMSE	1.423	1.625	1.793	1.917	2.255	2.428	2.512	2.570	2.607	2.656
DASTGN (Gao et al., 2023a)	MAE	1.039	1.184	1.297	1.387	1.662	1.806	1.900	1.945	1.995	2.028
	RMSE	1.384	1.572	1.721	1.829	2.170	2.338	2.449	2.498	2.554	2.600
DLinear	MAE	1.145	1.306	1.432	1.528	1.798	1.937	2.022	2.080	2.124	2.155
	RMSE	1.528	1.745	1.913	2.037	2.366	2.512	2.604	2.666	2.713	2.748
EMD-SVRCKH	MAE	1.111	1.311	1.432	1.526	1.788	1.919	1.998	2.051	2.090	2.119
	RMSE	1.489	1.755	1.909	2.027	2.344	2.495	2.587	2.650	2.695	2.730
Graph WaveNet	MAE	1.101	1.265	1.386	1.487	1.762	1.901	1.951	1.992	2.089	2.124
	RMSE	1.467	1.685	1.852	1.982	2.304	2.466	2.554	2.582	2.684	2.717
Historical Inertia	MAE	1.139	1.301	1.405	1.511	1.773	1.912	2.007	2.081	2.109	2.114
	RMSE	1.494	1.704	1.843	1.977	2.304	2.467	2.571	2.637	2.678	2.687
MTGNN	MAE	1.091	1.237	1.351	1.454	1.724	1.864	1.935	1.990	2.036	2.059
	RMSE	1.454	1.650	1.801	1.936	2.267	2.436	2.515	2.579	2.632	2.657
Multi LSTMs	MAE	1.312	1.645	1.914	2.129	2.610	2.748	2.793	2.818	2.842	2.867
	RMSE	1.663	2.079	2.415	2.679	3.257	3.420	3.477	3.510	3.540	3.573
PDCNN	MAE	2.025	2.026	2.385	2.551	2.959	3.011	3.012	2.971	2.918	2.877
	RMSE	2.561	2.562	3.033	3.243	3.750	3.824	3.833	3.789	3.727	3.675
SGNN	MAE	2.542	2.562	2.573	2.578	2.583	2.618	2.666	2.695	2.712	2.716
	RMSE	3.222	3.246	3.264	3.270	3.275	3.328	3.392	3.431	3.453	3.458
STGN (Geng et al., 2021)	MAE	1.084	1.281	1.407	1.523	1.809	1.942	2.046	2.073	2.137	2.189
	RMSE	1.430	1.697	1.863	2.013	2.358	2.514	2.631	2.649	2.717	2.771
TPA-LSTM	MAE	1.203	1.552	1.803	1.984	2.432	2.667	2.836	2.959	3.027	3.045
	RMSE	1.562	1.997	2.319	2.544	3.082	3.383	3.598	3.745	3.825	3.842
Wavelet-DBN-RF	MAE	1.451	1.597	1.749	1.836	2.087	2.162	2.200	2.217	2.232	2.243
	RMSE	1.855	2.038	2.226	2.328	2.617	2.703	2.744	2.766	2.788	2.798

be sometimes more feasible than accurately forecasting price values. In this case, assuming a daily granularity, a rise ("up") can be considered to occur when the next trading day's closing price (p_t) is at least 0.55 % higher than the previous day's closing price (p_{t-1}), whereas if p_t is more than 0.50 % lower than p_{t-1}, the price movement can be classified as a "down". Otherwise, it is classified as "neutral". All the selected GNN papers addressing stock prices indeed approach the price forecasting problem from a classification perspective. Another distinctive aspect in this group of papers is that researchers usually evaluate, among others, how their predictions affect the stability of investment returns over a specified period. This is commonly done through trading simulations in the test set, evaluated with metrics such as the Sharpe ratio and overall returns (Cheng et al., 2022; Huang et al., 2022; Pang et al., 2023; Sun et al., 2023; Xiang et al., 2022). These simulations require modeling rather than forecasting.

An examination of the selected papers indicates an interest in the application of spatio-temporal GNNs in Finance which starts from 2022. Two of the papers were published in *IEEE Access* by IEEE, while the remaining ones appeared in various other journals. The only two conference papers of this group were presented at CIKM.

5.3.2. Datasets

The number of datasets in this group is limited. The links to the public datasets referenced in the selected papers are listed in Table 14.

All the listed datasets represent collections of stock indices. The most common datasets include the China Securities Index (CSI), the 100 and 500 Standard and Poor's (S&P) indices, and the 100 and 300 China A-Shares indices. Many studies also include exogenous data, such as other market data, events, and news. News can be processed by some language model like BERT (as in Cheng et al., 2022; Huang et al., 2022; Lei & Song, 2024). Most of the data have a granularity of 1 day, and the forecasting horizon is also generally 1 day. One of the selected papers (Tian et al., 2023) analyses longer time horizons for stock forecasting. As for pre-processing techniques, half of the selected papers use normalization techniques, including min-max normalization, Z-score normalization, and logarithmic normalization.

Table 13
Comparison of the average accuracy of the different models on the Chinese AQI dataset for time horizons from 1 to 6 hours ahead, expressed in terms of MAE and RMSE. The smallest errors are underlined. Numbers from the original papers.

Model	Metrics	1 h	2 h	3 h	4 h	5 h	6 h
AirFormer	MAE	5.95	9.31	11.87	13.87	15.52	16.95
	RMSE	11.49	17.23	21.32	24.31	26.72	28.71
FGA	MAE	5.87	9.14	11.71	13.75	15.42	16.80
	RMSE	11.36	17.01	21.05	24.09	26.55	28.52
GAGNN (Chen et al., 2023d)	MAE	5.56	8.59	10.80	12.52	13.91	15.10
	RMSE	10.81	16.17	19.84	22.51	24.63	26.37
GC-LSTM	MAE	5.95	9.16	11.58	13.46	15.00	16.31
	RMSE	11.91	16.98	20.82	23.69	25.97	27.82
GWNet	MAE	5.76	9.64	12.79	15.30	17.28	18.81
	RMSE	11.27	17.57	22.31	25.75	28.52	30.48
HGCN	MAE	5.70	9.09	11.73	13.84	15.55	16.95
	RMSE	11.18	17.09	21.33	24.52	26.99	28.94
HighAir	MAE	5.50	8.52	10.81	12.50	14.00	15.09
	RMSE	10.80	16.10	19.85	22.70	24.91	26.40
INNGNN (Ding & Noh, 2023)	MAE	5.48	8.49	10.67	12.34	13.72	14.91
	RMSE	10.70	16.03	19.66	22.29	24.37	26.11
LSTM	MAE	6.50	10.26	13.18	15.52	17.40	18.91
	RMSE	13.85	19.26	23.52	26.83	29.46	31.55
MegaCRN	MAE	5.38	8.76	10.80	12.73	14.46	16.03
	RMSE	10.64	16.46	19.92	22.82	25.45	27.60
SHARE	MAE	5.84	9.07	11.49	13.35	14.74	15.79
	RMSE	11.27	16.84	20.77	23.60	25.80	27.38
XGBoost	MAE	6.85	10.89	13.99	16.27	18.14	19.56
	RMSE	14.25	19.80	24.72	28.14	30.63	33.44

Table 14
List of public datasets in the "Finance" group and their corresponding links.

Dataset	Used in	Link
China A-Shares	(Wang et al., 2023f), (Sun et al., 2023), (Cheng et al., 2022) and (Lei & Song, 2024)	https://finance.sina.com.cn/stock
CSI 100 index	(Tian et al., 2023)	https://tushare.pro/
CSI 300 index	(Huang et al., 2022), (Tian et al., 2023), (Chen et al., 2024b) and (Xiang et al., 2022)	https://global.csmar.com/
Nordpool dataset	(Sharma et al., 2022)	https://www.nordpoolgroup.com/
S&P 100 index	(Tian et al., 2023)	https://finance.yahoo.com/
S&P 500 index	(Huang et al., 2022) and (Xiang et al., 2022)	https://finance.yahoo.com/
Russell 1K index	(Tian et al., 2023)	https://finance.yahoo.com/
Russell 3K index	(Tian et al., 2023)	https://finance.yahoo.com/

5.3.3. Types of models

In terms of the taxonomy of the proposed GNN models, 7 out of 14 papers utilize attentional GNNs, 6 papers employ convolutional GNNs, and another one (Sharma et al., 2022) does not allow us to specify the classification of the model within the proposed taxonomy. As for the graph structure, some papers use models which learn the graph structure themselves (e.g., Chen et al., 2024b; Lei & Song, 2024; Li & Yao, 2022; Tian et al., 2023), whereas some others define it a priori, based on the relationships between companies and stocks (e.g., Huang et al., 2023c; Wang et al., 2023f; Yang et al., 2023d). One paper (Ye et al., 2022) examines how graph structures change across different observation scales, based on the idea that variable correlations observed over short timescales may differ significantly from those seen over longer periods.

Half of the papers deal with a stock movement classification problem, so the most commonly used loss function is cross entropy. The majority of the papers explicitly indicate that Python is the programming language utilized, with nearly half employing PyTorch, and a few utilizing TensorFlow. Only Wang et al. (2023f) provide a link to the source code of the proposed models, which is the knowledge graph with graph convolution neural network (KG-GCN) model, available at https://github.com/Gjl12321/KG_GCN_Stock_Price_Trend_Prediction_System.

5.3.4. Benchmark models

Table 15 displays the benchmark models utilized in the "Finance" group by a minimum of two of the selected papers.

It is evident that there is no consensus regarding the most appropriate benchmark model to use, especially of GNN type. The limited number of GNN-based benchmarks can be attributed to the fact that GNN models have not been extensively explored in the financial domain. The most common benchmark is the LSTM network, which is considered an effective approach for processing long term information in time series. The most commonly used GNN model is a vanilla graph convolutional network (GCN), followed by a more complex hierarchical graph attention network (HATS) proposed by Kim et al. (2019). The HATS model was proposed for predicting stock movements using relational data. It aggregates information from different types of relationships among data and incorporates this information into each stock representation. From an architectural point of view, the model starts with employing LSTM and GRU networks as feature extraction modules. Next, a hierarchical GNN-based architecture is designed to capture the significance of neighboring nodes and relation type across different layers. Finally, the node representations are fed into a task-specific module, which can be implemented as a simple linear transformation layer. The source code for the HATS model is available at https://github.com/dmis-lab/hats.

5.3.5. Results

The accuracy of the proposed classification models is primarily evaluated in terms of accuracy, precision and F1 score. The only two papers with results which can be compared are Wang et al. (2023f) and Sun et al. (2023), which study 758 frequently traded stocks collected from the A-share market in China from January 2013 to December 2019 (available at https://finance.sina.com.cn/stock). These two papers com-

Table 15
List of benchmark models in the "Finance" group divided per category.

Category	Model	Used in
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	(Yang et al., 2023d) and (Niu et al., 2024)
	Mean reversion (MR)	(Wang et al., 2023f) and (Sun et al., 2023)
Non-GNN machine learning methods	Convolutional neural network (CNN)	(Huang et al., 2022) and (Li & Yao, 2022)
	Dual-stage attention-based recurrent neural network (DARNN)	(Wang et al., 2023f) and (Sun et al., 2023)
	Feed-forward neural network (FNN)	(Huang et al., 2022), (Yang et al., 2023d), (Niu et al., 2024) and (Lei & Song, 2024)
	Gated recurrent unit (GRU)	(Pang et al., 2023), (Yang et al., 2023d), (Chen et al., 2024b) and (Xiang et al., 2022)
	Long-short term memory network (LSTM)	(Huang et al., 2022), (Tian et al., 2023), (Wang et al., 2023f), (Li & Yao, 2022), (Sun et al., 2023), (Huang et al., 2023c), (Yang et al., 2023d), (Niu et al., 2024) and (Xiang et al., 2022)
	Support vector machine (SVM)	(Li & Yao, 2022), (Yang et al., 2023d), (Niu et al., 2024) and (Lei & Song, 2024)
	Transformer (Vaswani et al., 2017)	(Chen et al., 2024b) and (Xiang et al., 2022)
GNN methods	Graph convolutional network (GCN)	(Huang et al., 2022), (Pang et al., 2023), (Tian et al., 2023), (Li & Yao, 2022), (Yang et al., 2023d) and (Chen et al., 2024b)
	Financial graph attention network (FinGAT) (Hsu et al., 2022)	(Pang et al., 2023) and (Tian et al., 2023)
	Hierarchical graph attention network (HATS) (Kim et al., 2019)	(Tian et al., 2023), (Wang et al., 2023f), (Sun et al., 2023) and (Xiang et al., 2022)
	Multivariate time series forecasting with graph neural network (MTGNN) (Wu et al., 2020c)	(Tian et al., 2023) and (Chen et al., 2024b)
	Spatiotemporal hypergraph convolution network (STHGCN) (Sawhney et al., 2020)	(Wang et al., 2023f) and (Sun et al., 2023)
	Temporal graph convolution (TGC) (Feng et al., 2019)	(Wang et al., 2023f) and (Xiang et al., 2022)

Table 16
Comparison of the average accuracy of the different models on the A-share market in China with 20 training days as records, expressed in terms of accuracy, precision, recall, and F1 score. The best results are underlined.

Model	Accuracy	Precision	Recall	F1 score
DARNN	38.41 %	37.99 %	39.24 %	38.60 %
GCN + LSTM	37.30 %	39.28 %	34.16 %	36.54 %
HATS	38.85 %	38.70 %	35.06 %	36.78 %
HGTAN	40.02 %	41.77 %	39.03 %	40.32 %
KG-GCN (Wang et al., 2023f)	<u>51.38 %</u>	<u>65.72 %</u>	31.45 %	39.27 %
LSTM	35.03 %	36.43 %	34.23 %	35.20 %
MOM	35.73 %	35.19 %	32.82 %	33.96 %
MONEY (Sun et al., 2023)	39.90 %	43.92 %	<u>40.61 %</u>	<u>42.20 %</u>
MR	35.32 %	38.03 %	33.60 %	35.68 %
SFM	34.54 %	26.93 %	33.32 %	29.49 %
STHGCN	38.45 %	37.22 %	32.82 %	34.87 %
TGC	37.81 %	36.96 %	34.49 %	35.67 %

pare the results obtained by using 5, 10 and 20 trading days as records. For sake of simplicity, a comparison of the accuracy of the models in the two papers with 20 days only is provided in Table 16.

The two best models are the knowledge graph and graph convolution neural network (KG-GCN) (Wang et al., 2023f) and the stock price movement prediction via convolutional network with adversarial hypergraph model (MONEY) (Sun et al., 2023), depending on the metrics considered. The KG-GCN model first constructs a knowledge graph to represent the semantic relationships and quantify correlations between stocks. Then a community detection module based on GCN node embeddings and K-means clustering is used to group similar stocks together. Finally, the historical prices of similar stocks are fed into LSTM and GRU networks to predict stock price trends. The MONEY model is composed of a convolutional GNN and an hypergraph convolution network to capture complex relations among similar stocks.

5.4. Health

The fourth thematic group of papers is "Health", which includes 23 out of 366 publications. These papers focus on critical aspects of health monitoring, disease modeling, and diagnostic tools, with particular emphasis on the spread and diagnosis of disease. All the papers working with functional magnetic resonance imaging (fMRI) data were excluded from the analysis, as the dataset was generated as image sequences rather than time series. This key difference in data structure makes them less relevant to the spatio-temporal focus of this review.

5.4.1. Overview

Applications of GNNs to the "Health" thematic group have been studied starting from 2021. The reason of this expansion may be attributed to two key factors. The first factor is the growing presence of sensors in hospitals, which enable the collection of multivariate time series signals, which can be used for the timely diagnosis of chronic diseases. The second factor is the spread of the COVID-19 pandemic, which motivated researchers to investigate and to forecast the spread of the virus. Epidemic forecasting is indeed the most common topic among the selected papers. The prediction of epidemics presents two significant challenges. First, epidemics' seasonality can vary greatly over time, and they can manifest with different intensities and durations. Second, occasional pandemics can disrupt established patterns even for years. These complexities make the forecasting task more difficult, and non-GNN machine learning, and GNN models themselves, have been studied to address this issue. Moreover, the spread of large-scale human diseases is closely related to both the mobility patterns of populations and the demographic characteristics of residents in different regions (Yanqin et al., 2024). Consequently, the application of GNN models to epidemic dynamics appears to be a suitable approach for analyzing and addressing such data. A common reference model for epidemic prediction is the SIR model (Kermack & McKendrick, 1927), an acronym referring to the state of the health of individuals. The three letters of the acronym stand for susceptible (S), infectious (I), and recovered (R). Namely, the SIR model divides the population into individuals who are susceptible to the disease, those who are infected and can spread it, and those who have recovered and are now immune. It uses a system of differential equations to describe how the disease spreads spatially and changes in time. The main advantage of this model is its inherent interpretability; it produces coefficients that are easy to interpret. However, its strong and simplistic assumptions also restrict its forecasting capability (Zheng et al., 2021). In general,

Table 17
List of public datasets in the "Health" group and their corresponding links.

Dataset	Used in	Link
African COVID-19 dataset	(Liu et al., 2024d)	https://www.worldometers.info/coronavirus/
Bonn dataset	(Wang et al., 2023c)	http://dx.doi.org/10.1103/PhysRevE.64.061907 (source paper)
Brazilian COVID-19 data	(Oliveira et al., 2022)	https://github.com/lcaldeira/GrafoBrasilCovid
CDC US-State	(Zhu et al., 2024b) and (Deng et al., 2020)	https://gis.cdc.gov/grasp/fluview/fluportaldashboard.html
Chickenpox	(Liu et al., 2024d) and (Hy et al., 2022)	https://www.kaggle.com/datasets/die9origephit/chickenpox-cases-hungary
CSSE COVID-19	(Segovia Dominguez et al., 2021), (Ma et al., 2022) and (Zheng et al., 2021)	https://github.com/CSSEGISandData/COVID-19
EEG DEAP dataset	(Guo & Wang, 2024)	http://www.eecs.qmul.ac.uk/mmv/datasets/deap/download.html
eICU	(Xu et al., 2022)	https://doi.org/10.1038/sdata.2018.178 (source paper)
European COVID-19 dataset	(Liu et al., 2024d)	https://www.worldometers.info/coronavirus/
ILI IDWR Japan-Prefecture	(Zhu et al., 2024b) and (Deng et al., 2020)	https://tinyurl.com/y5dt7stm
ILI US-HHS US-Regional	(Zhu et al., 2024b) and (Deng et al., 2020)	https://tinyurl.com/y39tog3h
ISRUC-Sleep Subgroup III (ISRUC-S3)	(Wang et al., 2023d)	https://sleeptight.isr.uc.pt/
Japan COVID-19	(Mao et al., 2024)	https://github.com/swsoyee/2019-ncov-japan
Montreal archive of sleep studies (MASS-SS3)	(Wang et al., 2023d)	http://www.ceams-carsm.ca/en/MASS
Meta COVID-19 data	(Zhu et al., 2024b) and (Hy et al., 2022)	https://dataforgood.fb.com/tools/disease-prevention-maps/
MIMIC-IV	(Xu et al., 2022)	https://physionet.org/content/mimiciv/2.0/
Nytimes COVID-19 data	(Li et al., 2022e) and (Yanqin et al., 2024)	https://github.com/nytimes/covid-19-data
OxCGRT dataset	(Kim et al., 2024b)	https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker
Parkinson's progression markers initiative (PPMI)	(Zhang et al., 2023g)	http://www.ppmi-info.org/
Parkinson speech dataset (PS)	(Zhang et al., 2023g)	https://doi.org/10.1109/jbhi.2013.2245674 (source paper)
SJTU emotion EEG dataset (SEED)	(Zhu et al., 2024a), (Guo & Wang, 2024) and (Wang et al., 2023d)	https://bcmi.sjtu.edu.cn/home/seed/
Spanish COVID-19 data	(Murphy et al., 2021)	https://cnecovid.isciii.es/
Spikes and slow waves (SSW)	(Wang et al., 2023c)	http://dx.doi.org/10.1109/ICDM50108.2020.00067 (source paper)
TUH EEG seizure corpus	(Cai et al., 2023)	https://isip.piconepress.com/projects/nedc/html/tuh_eeg/
US COVID-19 Johns Hopkins[2]	(Mao et al., 2024)	https://github.com/CSSEGISandData/COVID-19
US COVID-19 tracking project	(Kim et al., 2024b)	https://covidtracking.com/data/national
US COVID-19 vaccinations	(Li et al., 2022e)	https://ourworldindata.org/us-states-vaccinations[†]
US influenza	(Zhang et al., 2023c)	https://github.com/aI-area/DVGSN/tree/main/dataset

some papers use it as benchmark (e.g., Mao et al., 2024; Yanqin et al., 2024; Yu et al., 2023).

One study (Segovia Dominguez et al., 2021) also analyzes how air quality and satellite observations of temperature and humidity relate to COVID-19 mortality and severity.

Other papers in this section focus on different types of time series, such as electroencephalogram (EEG) data for epilepsy detection (Cai et al., 2023; Chen et al., 2022a; Wang et al., 2023c) or emotion recognition (Guo & Wang, 2024; Wang et al., 2023d; Zhu et al., 2024a). While emotion recognition may not seem directly related to the "Health" topic, it is included here because it relies on EEG data. The use of EEG in emotion recognition helps to identify more accurately true emotional states, as there physiological signals cannot be consciously controlled in the same way as facial expressions, tone of voice, or body posture (Zhu et al., 2024a).

The selected papers were each published in different journals, with one paper per journal, primarily in the field of computer science. In terms of conference venues, KDD and CIKM are the two most popular, with three papers each.

5.4.2. Datasets

Table 17 provides a list of the public datasets utilized in the selected papers, along with links for accessing them[2].

Only few subsets of papers in this thematic group use the same dataset, but none of the proposed models yield comparable results. Most of the datasets are related to COVID-19 and have a daily time granularity. In addition, some papers (Ma et al., 2022; Oliveira et al., 2022; Segovia Dominguez et al., 2021; Xu et al., 2022; Yanqin et al., 2024; Yu et al., 2023; Zhang et al., 2023g) include exogenous variables that can be either context-related (e.g., geography, population, health conditions, vaccinations, economic factors, air quality), or specific to a single patient (including personal information such as age, gender, and medical conditions). A paper that undertakes an in-depth study of exogenous variables is Kim et al. (2024b). The authors categorize these variables as holiday variables, time categorical variables (e.g., categorical week and month, and the number of days and weeks since the start of the dataset), and policy variables (e.g., school and workplace closing, movement restrictions, face coverings, and vaccination policies). They carry on a significance analysis of these variables, and explore the correlation among the significant ones. The COVID-19 policy dataset (OxCGRT) which includes three years of 23 policy indicators across more than 180 countries is available at https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker.

5.4.3. Types of models

As for the taxonomy of the proposed models, 18 out of 23 papers use a convolutional GNN architecture. Three papers use a pure attentional model, while two other papers present a hybrid convolutional-attentional architecture. Different approaches are used to define the graph structure. Some papers base their graphs on the geographical distribution of the data (as in Hy et al., 2022; Oliveira et al., 2022; Segovia Dominguez et al., 2021; Yu et al., 2023; Zhang et al., 2023g), and others use models that learn the graph structure directly (as in Kim et al., 2024b; Li et al., 2022e; Ma et al., 2022; Mao et al., 2024; Zhang et al., 2023c). There is also a paper that uses a variant of the visibility algorithm (Wang et al., 2023c). In half of the cases, the graph is static, while the dynamic graph approach appears more frequently in the papers from 2024.

In terms of programming languages, the community of the "Health" thematic group uses only Python with PyTorch. As for the choice of the loss functions, MSE is typically used for prediction tasks, and cross entropy is used for classification tasks. Table 18 shows the links to the related source codes.

[2] This dataset includes multiple sources.

Table 18
List of source codes of the "Health" models in the review.

Model	Link
Backbone-based dynamic spatio-temporal graph neural network (BDSTGNN) (Mao et al., 2024)	https://github.com/JkMaoya/BDSTGNN
DCRNN for COVID-19 forecasting (Segovia Dominguez et al., 2021)	https://github.com/Covid-19-papers/Recurrent-Graph-Neural-Network-on-COVID-19\protect\penalty-\@M-and-NASA-Satellite-data
Deep learning of contagion dynamics on complex networks (Murphy et al., 2021)	https://doi.org/10.5281/zenodo.4974521
Dynamic virtual graph significance networks (DVGSN) (Zhang et al., 2023c)	https://github.com/aI-area/DVGSN
Ordinary differential equation in graph neural networks (GNNODENet) (Yanqin et al., 2024)	https://github.com/xiongzhangxyq/GNNODENet
Hierarchical spatial-temporal framework for COVID-19 trend forecasting (HierST) (Zheng et al., 2021)	https://github.com/shun-zheng/HierST
Recurrent graph gate fusion transformers (ReGraFT) (Kim et al., 2024b)	https://github.com/mfriendly/ReGraFT
Sparse spectra graph convolutional network (SSGCNet) (Wang et al., 2023c)	https://github.com/anonymous2020-source-code/WNFG-SSGCNet-ADMM
Spatial-temporal graph convolutional network (STGCN) (Oliveira et al., 2022)	https://github.com/lcaldeira/CovidPandemicForecasting
Time-aware context-gated graph attention network (T-ContextGGAN) (Xu et al., 2022)	https://github.com/OwlCitizen/TContext-GGAN
Temporal multiresolution graph neural networks (TMGNN) (Hy et al., 2022)	https://github.com/bachnguyenTE/temporal-mgn

5.4.4. Benchmark models

Table 19 lists the benchmark models in the "Health" group that are discussed in at least two papers.

There are no particularly outstanding benchmark models, and the ones categorized as GNNs appear only in papers from 2024. This is due to the fact that in the past years GNNs have not been extensively explored in the context of health. The most widely used GNN-based benchmark is the diffusion convolutional recurrent neural network (DCRNN), proposed by Li et al. (2018) for traffic forecasting. The model aims to capture spatial dependencies using bidirectional random walks on the graph (whose adjacency matrix is based on node proximity), and temporal dependencies using an encoder-decoder architecture with scheduled sampling. The source code for the DCRNN model is available at https://github.com/liyaguang/DCRNN.

5.4.5. Results

In each paper, the authors claim that the proposed GNN-based model outperforms the benchmarks. The most common error metrics are the MAE and the MSE for forecasting problems and accuracy, sensitivity and specificity for classification problems. The forecasting horizon spans from 1 day to more than 10 weeks ahead. A comparison of the accuracy of the different models is not possible due to the lack of common benchmark datasets.

5.5. Mobility

The thematic group that includes the largest number of papers identified by our query (102 out of 366) is "Mobility", which regards the movement of people. It includes urban traffic, air travel, and bicycle demand, among other applications. Given the large number of articles in this group, a more detailed comparison of benchmarks, models, and results can be provided.

5.5.1. Overview

Early traffic prediction is essential for improving the efficiency of transportation systems, helping drivers plan their trips more effectively, and, in the context of cities, preventing urban congestion. The advent of smart cities infrastructures and transportation systems has contributed to the collection of rich data from road sensors. Making accurate traffic forecasts is challenging, due to constantly changing traffic patterns over time and space, as well as the influence of external factors such as weather conditions and special events. Unlike statistical and non-GNN machine learning models, GNNs can be particularly effective for traffic forecasting due to their ability to model complex relationships in spatial and temporal domain. The increasing number of papers published each year in this thematic group reflects both the growing research interest in this field and the growing confidence in GNN models. The most commonly investigated areas regard urban traffic (approximately 1/4 of the papers), especially urban traffic flow and urban traffic speed. Among the journals where the selected papers were published the most common are *Applied Intelligence* by Springer, *ACM Transactions on Knowledge Discovery from Data*, both by the Association for Computing Machinery, and *IEEE Transactions on Intelligent Transportation Systems* by the Institute of Electrical and Electronics Engineers, with 6 out of 66 papers each. The three conference venues with the highest number of papers are CIKM with 13 papers, SIGSPATIAL with 9 papers, and KDD with 8 papers.

5.5.2. Datasets

Table 20 provides a list of the public datasets mentioned in the selected papers, along with the links to access them.

The most popular datasets used in this group are those provided by the California Transportation Agency Performance Measurement System (PeMS, available at http://pems.dot.ca.gov/), which include various versions differing in time range, spatial coverage, and number of sensors, and the one called METR-LA, collected from loop detectors along the Los Angeles County highway. The number of sensors is in the hundreds, and such is also the number of nodes in the graph. For a more detailed overview of the benchmark datasets in the traffic domain, see Jiang et al. (2021). Other common public traffic datasets can be found at https://web.archive.org/web/20241212092408/https://paperswithcode.com/task/traffic-prediction. As to external data, the most commonly used are data on weather conditions, time information (time of day and day of week) and events (e.g., holidays), as well as information about the road network, like points of interest.

The majority of the papers utilize data with a 5-minute granularity, and provide forecasts for horizons ranging from 5 minutes to 1 h ahead. In addition to imputation of missing values, in almost half of the cases the pre-processing of the data includes data normalization (min-max or Z-score normalization) and the selection of time windows regarding recent, daily and weekly data.

5.5.3. Types of models

As for the proposed models, 53 out of 102 belong to the pure convolutional GNN paradigm, followed by 21 hybrid convolutional-attention architectures, 20 attentional GNNs, and 1 recurrent GNN. Two papers use both convolutional and attentional models, and other five (Fang et al., 2021; Tang et al., 2022; Wang et al., 2024e; Wei et al., 2024a; Wölker et al., 2023) do not fall into a specific class. Regarding the definition of the graph structure, most of the papers discuss it in detail. Almost half of the papers published before 2024 are based on a pre-defined adjacency matrix, while the majority of papers since 2024 propose models that learn the adjacency matrix on their own, either from scratch or based on a pre-initialization (e.g., Jin et al., 2023a; Li et al., 2024a). Here, more than in any other thematic group, there are multiple ways to define the adjacency matrix. This can be made by taking into account the

Table 19
List of benchmark models in the "Health" group divided per category.

Category	Model	Used in
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	(Zhang et al., 2023c), (Yu et al., 2023), (Oliveira et al., 2022), (Liu et al., 2024d), (Zhu et al., 2024b), (Mao et al., 2024), (Hy et al., 2022), (Deng et al., 2020) and (Ma et al., 2022)
	Historical average (HA)	(Hy et al., 2022) and (Ma et al., 2022)
	Naive	(Oliveira et al., 2022) and (Hy et al., 2022)
	SIR model (Kermack & McKendrick, 1927)	(Yu et al., 2023), (Yanqin et al., 2024) and (Mao et al., 2024)
Non-GNN machine learning methods	Feed-forward neural network (FNN)	(Wang et al., 2023c) and (Zhang et al., 2023c)
	Bi-hemisphere domain adversarial neural network (Bi-DANN) (Li et al., 2021h)	(Zhu et al., 2024a) and (Guo & Wang, 2024)
	A novel bi-hemispheric discrepancy model for EEG emotion recognition (BiHDM) (Li et al., 2021g)	(Zhu et al., 2024a) and (Guo & Wang, 2024)
	Convolutional neural network and recurrent neural network with residual module (CNNRNN-Res) (Wu et al., 2018)	(Zhu et al., 2024b) and (Deng et al., 2020)
	Gated recurrent unit (GRU)	(Liu et al., 2024d), (Yanqin et al., 2024), (Mao et al., 2024) and (Kim et al., 2024b)
	Long-short term memory network (LSTM)	(Yu et al., 2023), (Li et al., 2022e), (Liu et al., 2024d), (Yanqin et al., 2024), (Chen et al., 2022a), (Wang et al., 2023d), (Hy et al., 2022), (Deng et al., 2020) and (Ma et al., 2022)
	Long-short term time series network (LSTNet) (Lai et al., 2018)	(Zhu et al., 2024b) and (Deng et al., 2020)
	MiniRocket (Dempster et al., 2021)	(Chen et al., 2022a) and (Cai et al., 2023)
	Random forest (RF)	(Zhang et al., 2023c) and (Wang et al., 2023d)
	Recurrent neural network (RNN)	(Xu et al., 2022), (Yanqin et al., 2024), (Zhu et al., 2024b) and (Deng et al., 2020)
	Recurrent neural network with attention (RNN + Att)	(Zhu et al., 2024b) and (Deng et al., 2020)
	Support vector machine (SVM)	(Xu et al., 2022), (Zhu et al., 2024a) and (Wang et al., 2023d)
	Time-Series representation learning framework via Temporal and Contextual Contrasting (TS-TCC) (Eldele et al., 2021)	(Chen et al., 2022a) and (Cai et al., 2023)
	Time series transformer (TST) (Zerveas et al., 2021)	(Li et al., 2022e) and (Cai et al., 2023)
GNN methods	Cross-location attention based graph neural network (ColaGNN) (Deng et al., 2020)	(Zhu et al., 2024b), (Mao et al., 2024) and (Kim et al., 2024b)
	CovidGNN (Kapoor et al., 2020)	(Mao et al., 2024) and (Ma et al., 2022)
	Diffusion convolutional recurrent neural network (DCRNN) (Li et al., 2018)	(Yu et al., 2023), (Yanqin et al., 2024), (Zhu et al., 2024b), (Kim et al., 2024b) and (Deng et al., 2020)
	Dynamical graph convolutional neural networks (DGCNN) (Song et al., 2020b)	(Zhu et al., 2024a), (Guo & Wang, 2024) and (Wang et al., 2023d)
	Graph attention network (GAT) (Veličković et al., 2018)	(Zhang et al., 2023c) and (Yanqin et al., 2024)
	Graph convolutional network (GCN)	(Yu et al., 2023) and (Yanqin et al., 2024)
	Regularized graph neural networks (RGNN) (Zhong et al., 2022)	(Zhu et al., 2024a) and (Guo & Wang, 2024)
	Spatio-temporal attention network for pandemic prediction (STAN) (Gao et al., 2021)	(Yanqin et al., 2024), (Mao et al., 2024) and (Ma et al., 2022)
	Spatio-temporal graph convolutional network (STGCN) (Yu et al., 2018)	(Yanqin et al., 2024) and (Deng et al., 2020)
	Spatial-temporal graph ODE networks (STGODE) (Fang et al., 2021)	(Yanqin et al., 2024) and (Mao et al., 2024)

structure of the road network, the actual flow of people, or a combination of different sources of information. More in detail, a first group of papers uses road connectivity (e.g., Fan et al., 2023; He & Shin, 2020a; Jiang et al., 2022; Sánchez-Rada et al., 2024; Zhang et al., 2022a; Zhang & Guo, 2022); second group uses spatial distance (e.g., Bui et al., 2022; Cao et al., 2022; Kong et al., 2024a; Lablack & Shen, 2023; Li et al., 2022a, 2023e; Lu et al., 2022a; Wu et al., 2024c); a third group incorporates extra information about the so-called points of interest (such as Li et al., 2022a; Xia et al., 2021b); a fourth group considers some similarity measures between the time series (e.g., Dai et al., 2023; Gu et al., 2023; Khaled et al., 2022; Liao et al., 2024c; Zhao et al., 2024), such as the correlation coefficient or cosine similarity; a fifth group directly uses the number of people traveling on the road at a given time step (e.g., Cai et al., 2022; Ding et al., 2022; Wang et al., 2021; Xia et al., 2021b), or a combination of different aspects (e.g., Huo et al., 2024; Li et al., 2024a). For a more detailed overview of graph construction techniques in traffic flow prediction models, the reader is referred to (Fan et al., 2025).

The two most common loss functions used to train the models are the MAE and the MSE. Few papers consider a combination of loss functions, especially when dealing with a model that has to learn the graph structure by itself (Chen et al., 2020b; Feng et al., 2024c; Gu & Deng, 2022; Lu et al., 2022b; Shao et al., 2022b). Not all papers specify the language or library used for writing the code. Among those that do that, Python is the most common language, with the majority using PyTorch, whereas only a few researchers use TensorFlow. In addition, a few papers provide a link to the source code for the proposed model. The papers that provide such links are listed in Table 21.

5.5.4. Benchmark models

Table 22 lists the benchmark models used within the papers in the "Mobility" thematic group. These benchmarks are categorized into

mathematical and statistical methods, non-GNN machine learning models, and GNN models, and only those appearing in more than two papers are included in the table.

As for the basic mathematical and statistical methods, two widely used benchmarks are the ARIMA model and the historical average model (HA), which uses the average of past observations as the forecast for future values. Despite their apparent simplicity, these benchmarks are sometimes shown to be very powerful, with an accuracy comparable to that of more complex models. As for the non-GNN machine learning models, LSTM networks are widely recognized as a type of recurrent neural network capable of handling long-term dependencies in traffic data. As for GNN-based models instead, the most used models are the spatio-temporal graph convolutional network (STGCN) (Yu et al., 2018), the diffusion convolutional recurrent neural network (DCRNN) (Li et al., 2018), Graph WaveNet (GWN) (Wu et al., 2019), and the attention-based spatial-temporal graph convolutional network (ASTGCN) (Guo

Table 20
List of public datasets in the "Mobility" group and their corresponding links.

Dataset	Used in	Link
Baoding dataset	(Zhang et al., 2024f)	https://github.com/usail-hkust/ASeer
BRN +	(Dan et al., 2024)	https://www.microsoft.com/en-us/research/publication/t-drive-trajectory-data-sample/
Bruxelles transport data	(Ramhormozi et al., 2022)	https://www.kaggle.com/datasets/giobbu/belgium-obu
Bureau of transportation statistics (BTS)	(Wu et al., 2024c) and (Wu et al., 2024b)	https://www.transtats.bts.gov/
CAAC flights	(Cai et al., 2022)	http://www.caac.gov.cn/index.html
Capital bike share	(Feng et al., 2024c)	https://ride.capitalbikeshare.com/system-data†
CarPark1918	(Jiang et al., 2024b)	https://github.com/JIANGYUE61610306/SAGDFN/tree/main/data/model
CD-HW	(Chen et al., 2020b)	https://doi.org/10.1109/ACCESS.2020.3027375 (source paper)
DiDi Beijing	(Wang et al., 2021) and (Han et al., 2024b)	https://github.com/didi/TrafficIndex
DiDi Chengdu	(Lu et al., 2022a), (Li et al., 2022c), (Lu et al., 2022b), (Hu et al., 2024b), (Li et al., 2021c) and (Lu et al., 2020)	https://gaia.didichuxing.com/†
Didi Shenzhen	(Lu et al., 2022b) and (Hu et al., 2024b)	https://outreach.didichuxing.com/app-outreach/CTIE
Divvy bike Chicago	(Feng et al., 2024c) and (He & Shin, 2020b)	https://ride.divvybikes.com/system-data†
Highways England	(Han et al., 2021)	http://tris.highwaysengland.co.uk/detail/trafficflowdata
Los-loop	(Liu et al., 2023c)	https://github.com/lehaifeng/T-GCN/tree/master/data
Lyft bike dataset	(Feng et al., 2024c)	https://www.lyft.com/bikes/bay-wheels/system-data
METR-LA	(Lu et al., 2022a), (Li et al., 2023e), (Li et al., 2023b), (Li et al., 2023d), (Lablack & Shen, 2023), (Kumar et al., 2023), (Guo et al., 2023b), (Zhang & Guo, 2022), (Khaled et al., 2022), (Chen et al., 2020b), (Bui et al., 2022), (Chen et al., 2025), (Bikram et al., 2024), (Kwak et al., 2024), (Li et al., 2024g), (Zhao et al., 2024), (Wei et al., 2024a), (Shin & Yoon, 2024), (Wang et al., 2024a), (Li et al., 2024a), (Shao et al., 2022b), (Jiang et al., 2024b), (Lu et al., 2022b), (Wang et al., 2020), (Jin et al., 2023d), (Shao et al., 2022c), (Zhu et al., 2023), (Hu et al., 2024b), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Zhou et al., 2024b), (Li et al., 2021d), (Chen et al., 2020a), (Ma et al., 2023), (Park et al., 2020) and (Wölker et al., 2023)	https://www.kaggle.com/datasets/annnnguyen/metr-la-dataset
NE-BJ	(Li et al., 2023b)	https://github.com/tsinghua-fib-lab/Traffic-Benchmark
NYC-Bike	(Xia et al., 2021b), (Li et al., 2022a), (Liang et al., 2023), (Feng et al., 2024c), (Wang et al., 2024e), (Liu et al., 2022a), (Gao et al., 2024a) and (Wu et al., 2023)	https://citibikenyc.com/system-data
NYC-Taxi	(Li et al., 2022a), (Liu et al., 2022a), (Gao et al., 2024a), (Wu et al., 2023), (Zhou et al., 2024b) and (Zhang et al., 2020c)	https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page
PeMS03	(Jin et al., 2023a), (Kumar et al., 2023), (Yang et al., 2023b), (Gu et al., 2023), (Zhao et al., 2023), (Gu & Deng, 2022), (Jakhmola et al., 2024), (Zhao et al., 2024), (Liao et al., 2024c), (Fang et al., 2024), (Fang et al., 2023a), (Lan et al., 2022), (Fang et al., 2021), (Liu et al., 2022a), (Fan et al., 2023), (Gao et al., 2024a), (Li et al., 2022b), (Dan et al., 2024), (Yu et al., 2024b) and (Hu et al., 2023)	https://www.kaggle.com/datasets/elmahy/pems-dataset
PeMS04 (PeMSD4)	(Dai et al., 2023), (Li et al., 2023e), (Zhang et al., 2022a), (Jin et al., 2023a), (Kumar et al., 2023), (Yang et al., 2023b), (Gu et al., 2023), (Khaled et al., 2022), (Zhao et al., 2023), (Gu & Deng, 2022), (Diao et al., 2023a), (Cao et al., 2022), (Li et al., 2024c), (Chen et al., 2025), (Jakhmola et al., 2024), (Wei et al., 2024b), (Li et al., 2024g), (Zhao et al., 2024), (Shin & Yoon, 2024), (Liao et al., 2024c), (Fang et al., 2024), (Shao et al., 2022b), (Han et al., 2021), (Fang et al., 2023a), (Shao et al., 2022c), (Lan et al., 2022), (Fang et al., 2021), (Bai et al., 2020), (Fan et al., 2023), (Gao et al., 2024a), (Zou et al., 2024a), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Dan et al., 2024), (Tang et al., 2022), (Yu et al., 2024b) and (Hu et al., 2023)	https://www.kaggle.com/datasets/elmahy/pems-dataset
PeMS07 (PeMSD7)	(Jin et al., 2023a), (Lablack & Shen, 2023), (Kumar et al., 2023), (Gu et al., 2023), (Zhao et al., 2023), (Gu & Deng, 2022), (Li et al., 2024c), (Zang et al., 2024), (Wei et al., 2024b), (Bikram et al., 2024), (Singh et al., 2024), (Zhao et al., 2024), (Wei et al., 2024a), (Shin & Yoon, 2024), (Li et al., 2024a), (Liao et al., 2024c), (Fang et al., 2024), (Jin et al., 2023d), (Fang et al., 2023a), (Lan et al., 2022), (Fang et al., 2021), (Fan et al., 2023), (Gao et al., 2024a), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Tang et al., 2022), (Yu et al., 2024b) and (Hu et al., 2023)	https://www.kaggle.com/datasets/elmahy/pems-dataset

Table 20
Continued

PeMS08 (PeMSD8)	(Dai et al., 2023), (Li et al., 2023e), (Jin et al., 2023a), (Yang et al., 2023b), (Gu et al., 2023), (Khaled et al., 2022), (Zhao et al., 2023), (Gu & Deng, 2022), (Diao et al., 2023a), (Cao et al., 2022), (Li et al., 2024c), (Chen et al., 2025), (Wei et al., 2024b), (Singh et al., 2024), (Li et al., 2024g), (Zhao et al., 2024), (Shin & Yoon, 2024), (Li et al., 2024a), (Liao et al., 2024c), (Fang et al., 2024), (Han et al., 2021), (Fang et al., 2023a), (Shao et al., 2022c), (Lan et al., 2022), (Fang et al., 2021), (Liu et al., 2022a), (Bai et al., 2020), (Fan et al., 2023), (Gao et al., 2024a), (Zou et al., 2024a), (Li et al., 2022b), (Dan et al., 2024), (Tang et al., 2022), (Li et al., 2021c), (Yu et al., 2024b), (Ma et al., 2023) and (Hu et al., 2023)	https://www.kaggle.com/datasets/elmahy/pems-dataset
PEMS-BAY	(Li et al., 2023b), (Li et al., 2023d), (Lablack & Shen, 2023), (Guo et al., 2023b), (Zhang & Guo, 2022), (Khaled et al., 2022), (Li et al., 2024c), (Chen et al., 2025), (Jakhmola et al., 2024), (Huo et al., 2024), (Zang et al., 2024), (Kwak et al., 2024), (Li et al., 2024g), (Zhao et al., 2024), (Shin & Yoon, 2024), (Wang et al., 2024a), (Li et al., 2024a), (Shao et al., 2022b), (Lu et al., 2022b), (Wang et al., 2020), (Jin et al., 2023d), (Shao et al., 2022c), (Zhu et al., 2023), (Hu et al., 2024b), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Li et al., 2021d), (Ma et al., 2023), (Park et al., 2020) and (Wölker et al., 2023)	https://zenodo.org/records/4263971
Q-Traffic	(Lu et al., 2022c)	https://github.com/JingqingZ/BaiduTraffic#Dataset
SafeGraph	(Hajisafi et al., 2023)	https://www.safegraph.com/
Seattle loop	(Shin & Yoon, 2024) and (Chen et al., 2020a)	https://github.com/zhiyongc/Seattle-Loop-Data
UVDS	(Bui et al., 2022)	https://doi.org/10.1007/978-3-030-73280-6_6 (source paper)
TaxiBJ	(Chen et al., 2020b), (Wang et al., 2024e) and (Chen et al., 2023e)	https://www.microsoft.com/en-us/research/publication/forecasting-citywide-crowd\protect\penalty-\@M-flows-based-big-data/
Taxi Shenzhen	(Liu et al., 2023c) and (Jiang et al., 2022)	https://github.com/lehaifeng/T-GCN/tree/master/data
TLC Taxi	(Liao et al., 2022)	https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page
Urban-core	(Shin & Yoon, 2024)	https://topis.seoul.go.kr/
Xiecheng delay	(Wu et al., 2024b)	https://pan.baidu.com/s/1dEPyMGh#list/path\protect\LY1\textdollar=\protect\LY1\textdollar=%2F
Zhuzhou dataset	(Zhang et al., 2024f)	https://github.com/usail-hkust/ASeer

Table 21
List of source codes of the "Mobility" models in the review.

Model	Link
3-Dimensional graph convolution network (3DGCN) (Xia et al., 2021b)	https://github.com/FIBLAB/3D-DGCN
Adaptive graph convolutional recurrent network (AGCRN) (Bai et al., 2020)	https://github.com/LeiBAI/AGCRN
Adaptive generalized PageRank graph neural network (AGP-GNN) (Guo et al., 2023b)	https://github.com/guoxiaoyuatbjtu/agp-gnn
Adaptive multigraph convolutional networks (AMGCN) (Li et al., 2024a)	https://github.com/hfimmortal/AMGCN
Asynchronous spatio-temporal graph convolutional network (ASeer) (Zhang et al., 2024f)	https://github.com/usail-hkust/ASeer
Automated dilated spatio-temporal synchronous graph network (Auto-DSTSGN) (Jin et al., 2023a)	https://github.com/jinguangyin/Auto-DSTSGN
BigST (Han et al., 2024b)	https://github.com/usail-hkust/BigST
Dynamic multi-view graph neural network for citywide traffic inference (CTVI+) (Dai et al., 2023)	https://github.com/dsj96/TKDD
Decoupled dynamic spatial-temporal graph neural network (D2STGNN) (Shao et al., 2022c)	https://github.com/zezhishao/D2STGNN
Domain adversarial spatial-temporal network (DastNet) (Tang et al., 2022)	https://github.com/YihongT/DASTNet
Dynamic graph convolutional recurrent network (DGCRN) (Li et al., 2023b)	https://github.com/tsinghua-fib-lab/Traffic-Benchmark
Deep Kalman filtering network (DKFN) (Chen et al., 2020a)	https://github.com/Fanglanc/DKFN
Dynamic and multi-faceted spatio-temporal graph convolution network (DMSTGCN) (Han et al., 2021)	https://github.com/liangzhehan/DMSTGCN
Dynamic spatial-temporal aware graph neural network (DSTAGNN) (Lan et al., 2022)	https://github.com/SYLan2019/DSTAGNN
Graph bootstrap (Gboot) (Gao et al., 2024a)	https://github.com/wangzz-yyzz/Gboot
Hierarchical information enhanced spatio-temporal (HIEST) (Ma et al., 2023)	https://github.com/VAN-QIAN/CIKM23-HIEST
Multi-step dependency relation (MSDR) (Liu et al., 2022a)	https://github.com/dcliu99/MSDR
Multi-range spatial-temporal transformer network (MultiSPANS) (Zou et al., 2024a)	https://github.com/SELGroup/MultiSPANS
Progressive graph convolutional network (PGCN) (Shin & Yoon, 2024)	https://github.com/yuyolshin/PGCN
Scalable adaptive graph diffusion forecasting network (SAGDFN) (Jiang et al., 2024b)	https://github.com/JIANGYUE61610306/SAGDFN
Scale-aware neural architecture search framework for MTS forecasting (SNAS4MTF) (Chen et al., 2025)	https://github.com/shangzongjiang/SNAS4MTF
Spatio-temporal adaptive gated graph convolution network (STAG-GCN) (Lu et al., 2020)	https://github.com/RobinLu1209/STAG-GCN
Spatial-temporal convolutional graph attention network (ST-CGA) (Zhang et al., 2020c)	https://github.com/jbdj-star/cga
Spatio-temporal causal graph attention network (STCGAT) (Zhao et al., 2023)	https://github.com/zsqZZU/STCGAT/tree/v1.0.0
STGNN enhanced by a scalable time series pre-training model (STEP) (Shao et al., 2022b)	https://github.com/zezhishao/STEP
Spatial-temporal graph ordinary differential equation networks (STGODE) (Fang et al., 2021)	https://github.com/square-coder/STGODE
Spatio-temporal graph mixformer (STGM) (Lablack & Shen, 2023)	https://github.com/mouradost/stgm
Spatio-temporal graph prompting (STGP) (Hu et al., 2024b)	https://github.com/hjf1997/STGP
Space-time separable graph convolutional network (STSGCN) (Wu et al., 2024b)	https://github.com/FraLuca/STSGCN
Spatio-temporal network with discrete wavelet transform (STWave) (Fang et al., 2023a)	https://github.com/LMissher/STWave
Sparse unstructured spatio temporal reconstruction (SUSTeR) (Wölker et al., 2023)	https://github.com/ywoelker/SUSTeR
Transferable graphs for traffics (TransGTR) (Jin et al., 2023d)	https://github.com/KL4805/TransGTR/
Two-level resolution neural network (TwoResNet) (Kwak et al., 2024)	https://github.com/semink/TwoResNet
Wavelet dynamic spatiotemporal aware graph neural network (W-DSTAGNN) (Jakhmola et al., 2024)	https://github.com/yash-jakhmola/w-dstagnn

Table 22
List of benchmark models in the "Mobility" group divided per category.

Category	Model	Used in
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	(Lu et al., 2022a), (Xia et al., 2021b), (Li et al., 2022a), (Li et al., 2022c), (Li et al., 2023b), (Liu et al., 2023c), (Liu et al., 2023b), (Li et al., 2023d), (Guo et al., 2023b), (Chen et al., 2020b), (Cai et al., 2022), (Cao et al., 2022), (Jiang et al., 2022), (Li et al., 2024c), (Chen et al., 2025), (Jakhmola et al., 2024), (Wang et al., 2024d), (Wei et al., 2024b), (Kwak et al., 2024), (Li et al., 2024g), (Wei et al., 2024a), (Li et al., 2024a), (Feng et al., 2024c), (Wang et al., 2024e), (Fang et al., 2024), (Jiang et al., 2024b), (Han et al., 2021), (Lu et al., 2022b), (Wang et al., 2020), (Jin et al., 2023d), (Fang et al., 2023a), (Zhu et al., 2023), (Fang et al., 2021), (Hu et al., 2024b), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Li et al., 2021d), (Chen et al., 2020a), (Ramhormozi et al., 2022), (Li et al., 2021c), (Zhang et al., 2020c), (Hu et al., 2023) and (Lu et al., 2020)
	Historical average (HA)	(Lu et al., 2022a), (Xia et al., 2021b), (Li et al., 2022a), (Li et al., 2022c), (Li et al., 2023b), (Wang et al., 2021), (Liu et al., 2023c), (Li et al., 2023d), (Lablack & Shen, 2023), (Zhang & Guo, 2022), (Zhao et al., 2023), (Diao et al., 2023a), (Cao et al., 2022), (Jiang et al., 2022), (Li et al., 2024c), (Chen et al., 2025), (Huo et al., 2024), (Wei et al., 2024b), (Li et al., 2024g), (Zhao et al., 2024), (Wei et al., 2024a), (Shin & Yoon, 2024), (Wu et al., 2024b), (Feng et al., 2024c), (Han et al., 2024b), (Wang et al., 2024e), (Fang et al., 2024), (Shao et al., 2022b), (Han et al., 2021), (He & Shin, 2020a), (Zhang et al., 2024f), (Lu et al., 2022b), (He & Shin, 2020b), (Wang et al., 2020), (Fang et al., 2023a), (Shao et al., 2022c), (Zhu et al., 2023), (Liu et al., 2022a), (Bai et al., 2020), (Hu et al., 2024b), (Li et al., 2021d), (Tang et al., 2022), (Chen et al., 2020a), (Hajisafi et al., 2023), (Ramhormozi et al., 2022), (Li et al., 2021c), (Lu et al., 2020) and (Ou et al., 2020)
	k-nearest neighbors (KNN)	(Dai et al., 2023), (Hu et al., 2024b) and (Lu et al., 2020)
	Naive	(Zhang et al., 2024f), (Hajisafi et al., 2023) and (Ou et al., 2020)
	Vector autoregression (VAR)	(Li et al., 2023e), (Li et al., 2023b), (Chen et al., 2020b), (Diao et al., 2023a), (Cao et al., 2022), (Li et al., 2024c), (Jakhmola et al., 2024), (Wei et al., 2024b), (Zhao et al., 2024), (Wu et al., 2024b), (Liao et al., 2024c), (Han et al., 2024b), (Fang et al., 2024), (Shao et al., 2022b), (Jiang et al., 2024b), (Han et al., 2021), (Wang et al., 2020), (Fang et al., 2023a), (Shao et al., 2022c), (Bai et al., 2020), (Zou et al., 2024a), (Li et al., 2022b), (Yu et al., 2024b), (Hu et al., 2023) and (Ou et al., 2020)
Non-GNN machine learning methods	Adaptive recurrent neural network (AdaRNN) (Du et al., 2021)	(Lu et al., 2022b) and (Hu et al., 2024b)
	Convolutional long-short term memory network (ConvLSTM) (Shi et al., 2015)	(Li et al., 2022c), (Feng et al., 2024c), (Hajisafi et al., 2023) and (Ou et al., 2020)
	Deep multi-view spatial-temporal network (DMVST-Net) (Yao et al., 2018)	(Li et al., 2022a), (Wang et al., 2024e) and (Zhang et al., 2020c)
	Feed-forward neural network (FNN)	(Lu et al., 2022a), (Dai et al., 2023), (Li et al., 2023b), (Xie et al., 2020b), (Liang et al., 2023), (Zhang & Guo, 2022), (Zhao et al., 2022a), (Lu et al., 2022c), (Chen et al., 2020b), (Chen et al., 2025), (Huo et al., 2024), (Sánchez-Rada et al., 2024), (Wei et al., 2024a), (Li et al., 2022b), (Li et al., 2023c), (Lu et al., 2020) and (Ou et al., 2020)
	Gated recurrent unit (GRU)	(Li et al., 2022c), (Li et al., 2023e), (Liu et al., 2023b), (Zhao et al., 2022a), (Lu et al., 2022c), (Diao et al., 2023a), (Cao et al., 2022), (Jiang et al., 2022), (Peng et al., 2024), (Zhang et al., 2024f), (Bai et al., 2020), (Tang et al., 2022) and (Li et al., 2021c)
	Long-short term memory network (LSTM)	(Lu et al., 2022a), (Li et al., 2022a), (Li et al., 2022c), (Li et al., 2023e), (Li et al., 2023b), (Liu et al., 2023b), (Jin et al., 2023a), (Li et al., 2023d), (Kumar et al., 2023), (Yang et al., 2023b), (Guo et al., 2023b), (Zhang & Guo, 2022), (Zhao et al., 2022a), (Khaled et al., 2022), (Zhao et al., 2023), (Chen et al., 2020b), (Gu & Deng, 2022), (Diao et al., 2023a), (Cao et al., 2022), (Li et al., 2024c), (Chen et al., 2025), (Jakhmola et al., 2024), (Huo et al., 2024), (Wang et al., 2024d), (Wei et al., 2024b), (Peng et al., 2024), (Kwak et al., 2024), (Li et al., 2024g), (Zhao et al., 2024), (Wei et al., 2024a), (Shin & Yoon, 2024), (Wang et al., 2024a), (Wu et al., 2024b), (Li et al., 2024a), (Liao et al., 2024c), (Fang et al., 2024), (Shao et al., 2022b), (Jiang et al., 2024b), (He & Shin, 2020a), (Zhang et al., 2024f), (He & Shin, 2020b), (Wang et al., 2020), (Fang et al., 2023a), (Shao et al., 2022c), (Zhu et al., 2023), (Lan et al., 2022), (Liu et al., 2022a), (Fan et al., 2023), (Zou et al., 2024a), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Wang et al., 2023e), (Li et al., 2021d), (Chen et al., 2020a), (Li et al., 2021c), (Li et al., 2023c), (Yu et al., 2024b), (Zhang et al., 2020c), (Hu et al., 2023), (Lu et al., 2020) and (Ou et al., 2020)
	Long-short term time series network (LSTNet) (Lai et al., 2018)	(Wang et al., 2021) and (Lablack & Shen, 2023)
	Multitask deep-learning (MDL) (Zhang et al., 2020a)	(Wang et al., 2024e) and (Zhou et al., 2024b)
	Recurrent neural network (RNN)	(Wang et al., 2024e), (Marisca et al., 2024), (He & Shin, 2020b) and (Wang et al., 2020)
	Seq2Seq (Sutskever et al., 2014)	(Xie et al., 2020b), (Lu et al., 2022c) and (Wang et al., 2024e)
	Spatial-temporal dynamic network (STDN) (Yao et al., 2019)	(Wang et al., 2024e) and (Zhang et al., 2020c)
	Spatial-temporal identity (STID) (Shao et al., 2022a)	(Guo et al., 2023b), (Zang et al., 2024), (Li et al., 2024g), (Wu et al., 2024c), (Zhu et al., 2023), (Wu et al., 2023) and (Wang et al., 2023e)
	Spatial and temporal normalization for multivariate time series forecasting (ST-Norm) (Deng et al., 2021)	(Guo et al., 2023b), (Gu et al., 2023), (Li et al., 2024c) and (Zang et al., 2024)
	Spatio-temporal residual networks (ST-ResNet) (Zhang et al., 2017b)	(Wang et al., 2024e) and (Zhang et al., 2020c)

Table 22
Continued

	Support vector regression (SVR)	(Li et al., 2023e), (Li et al., 2023b), (Liu et al., 2023c), (Li et al., 2023d), (Liao et al., 2022), (Cai et al., 2022), (Gu & Deng, 2022), (Jiang et al., 2022), (Chen et al., 2025), (Jakhmola et al., 2024), (Wang et al., 2024d), (Zhao et al., 2024), (Li et al., 2024a), (Liao et al., 2024c), (Fang et al., 2024), (Shao et al., 2022b), (Jiang et al., 2024b), (Wang et al., 2020), (Fang et al., 2023a), (Shao et al., 2022c), (Zou et al., 2024a), (Wu et al., 2023), (Li et al., 2022b), (Tang et al., 2022), (Chen et al., 2020a), (Ramhormozi et al., 2022), (Yu et al., 2024b), (Ma et al., 2023) and (Zhang et al., 2020c)
	Temporal convolutional network (TCN) (Bai et al., 2018)	(Feng et al., 2024c), (Fang et al., 2024), (Zhang et al., 2024f), (Fang et al., 2023a), (Lan et al., 2022), (Fan et al., 2023) and (Dan et al., 2024)
	Temporal 2D-variation modeling for general time series analysis (TimesNet) (Wu et al., 2023a)	(Wu et al., 2024c) and (Zhao et al., 2024)
	Transformer (Vaswani et al., 2017)	(Wei et al., 2024b), (Kong et al., 2024a) and (Zhou et al., 2024b)
	Extreme gradient boosting (XGBoost) (Chen & Guestrin, 2016)	(Dai et al., 2023), (Liang et al., 2023) and (Han et al., 2021)
GNN methods	Adaptive graph convolutional recurrent network (AGCRN) (Bai et al., 2020)	(Li et al., 2022c), (Li et al., 2023b), (Lablack & Shen, 2023), (Gu et al., 2023), (Lu et al., 2022c), (Zhao et al., 2023), (Gu & Deng, 2022), (Diao et al., 2023a), (Li et al., 2024c), (Jakhmola et al., 2024), (Zhao et al., 2024), (Shin & Yoon, 2024), (Han et al., 2024b), (Fang et al., 2024), (Kong et al., 2024a), (Jiang et al., 2024b), (Fang et al., 2023a), (Zhu et al., 2023), (Lan et al., 2022), (Fan et al., 2023), (Gao et al., 2024a), (Li et al., 2022b), (Dan et al., 2024), (Tang et al., 2022), (Chen et al., 2020a), (Li et al., 2023c) and (Hu et al., 2023)
	Attention-based spatial-temporal graph convolutional network (ASTGCN) (Guo et al., 2019)	(Lu et al., 2022a), (Li et al., 2022c), (Li et al., 2023e), (Li et al., 2023b), (Jin et al., 2023a), (Lablack & Shen, 2023), (Kumar et al., 2023), (Yang et al., 2023b), (Gu et al., 2023), (Zhao et al., 2022a), (Zhao et al., 2023), (Chen et al., 2020b), (Gu & Deng, 2022), (Diao et al., 2023a), (Cao et al., 2022), (Li et al., 2024c), (Wang et al., 2024d), (Wei et al., 2024b), (Bikram et al., 2024), (Singh et al., 2024), (Li et al., 2024g), (Zhao et al., 2024), (Wang et al., 2024a), (Liao et al., 2024c), (Feng et al., 2024c), (Han et al., 2024b), (Fang et al., 2024), (Kong et al., 2024a), (Shao et al., 2022b), (Jiang et al., 2024b), (Fang et al., 2023a), (Shao et al., 2022c), (Zhu et al., 2023), (Lan et al., 2022), (Fang et al., 2021), (Liu et al., 2022a), (Bai et al., 2020), (Fan et al., 2023), (Gao et al., 2024a), (Zou et al., 2024a), (Wu et al., 2023), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Dan et al., 2024), (Chen et al., 2020a), (Hajisafi et al., 2023), (Ramhormozi et al., 2022), (Li et al., 2023c), (Yu et al., 2024b), (Hu et al., 2023) and (Lu et al., 2020)
	Attention based spatial-temporal graph neural network (ASTGNN) (Guo et al., 2022a)	(Zang et al., 2024), (Zhao et al., 2024) and (Feng et al., 2024c)
	Automated spatio-temporal graph (AutoSTG) (Pan et al., 2021b)	(Jin et al., 2023a), (Chen et al., 2025), (Li et al., 2022b), (Chen et al., 2020a) and (Li et al., 2023c)
	Coupled layer-wise convolutional recurrent neural network (CCRNN) (Ye et al., 2021)	(Liu et al., 2022a) and (Wu et al., 2023)
	Decoupled dynamic spatial-temporal graph neural network (D2STGNN) (Shao et al., 2022c)	(Jiang et al., 2024b) and (Wölker et al., 2023)
	Dual-stage attention-based recurrent neural network (DA-RNN) (Qin et al., 2017)	(Li et al., 2022a) and (Xie et al., 2020b)
	Diffusion convolutional recurrent neural network (DCRNN) (Li et al., 2018)	(Lu et al., 2022a), (Xia et al., 2021b), (Li et al., 2022a), (Li et al., 2023b), (Liu et al., 2023c), (Jin et al., 2023a), (Li et al., 2023d), (Lablack & Shen, 2023), (Kumar et al., 2023), (Yang et al., 2023b), (Guo et al., 2023b), (Gu et al., 2023), (Zhang & Guo, 2022), (Khaled et al., 2022), (Lu et al., 2022c), (Zhao et al., 2023), (Chen et al., 2020b), (Bui et al., 2022), (Cai et al., 2022), (Gu & Deng, 2022), (Diao et al., 2023a), (Cao et al., 2022), (Li et al., 2024c), (Chen et al., 2025), (Jakhmola et al., 2024), (Huo et al., 2024), (Wang et al., 2024d), (Zang et al., 2024), (Wei et al., 2024b), (Peng et al., 2024), (Bikram et al., 2024), (Kwak et al., 2024), (Singh et al., 2024), (Li et al., 2024g), (Zhao et al., 2024), (Wei et al., 2024a), (Shin & Yoon, 2024), (Wang et al., 2024a), (Li et al., 2024a), (Liao et al., 2024c), (Han et al., 2024b), (Wang et al., 2024e), (Fang et al., 2024), (Shao et al., 2022b), (Jiang et al., 2024b), (Han et al., 2021), (Zhang et al., 2024f), (Wang et al., 2020), (Fang et al., 2023a), (Shao et al., 2022c), (Zhu et al., 2023), (Lan et al., 2022), (Fang et al., 2021), (Gupta et al., 2023), (Liu et al., 2022a), (Bai et al., 2020), (Hu et al., 2024b), (Fan et al., 2023), (Gao et al., 2024a), (Zou et al., 2024a), (Wu et al., 2023), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Wang et al., 2023e), (Li et al., 2021d), (Tang et al., 2022), (Chen et al., 2020a), (Hajisafi et al., 2023), (Li et al., 2023c), (Yu et al., 2024b), (Ma et al., 2023), (Hu et al., 2023), (Lu et al., 2020), (Park et al., 2020) and (Ou et al., 2020)
	Deep spatial-temporal network (DeepST) (Zhang et al., 2016)	(Wang et al., 2024e) and (Zhang et al., 2020c)
	Dynamic graph convolutional recurrent network (DGCRN) (Li et al., 2023b)	(Lablack & Shen, 2023), (Li et al., 2024c), (Li et al., 2024a) and (Shao et al., 2022c)
	Dynamic and multi-faceted spatiotemporal graph convolution network (DMSTGCN) (Han et al., 2021)	(Shin & Yoon, 2024) and (Li et al., 2024a)
	Dynamic spatial-temporal aware graph neural network (DSTAGNN) (Lan et al., 2022)	(Zhao et al., 2023), (Jakhmola et al., 2024), (Wei et al., 2024b), (Han et al., 2024b), (Hu et al., 2024b), (Fan et al., 2023), (Gao et al., 2024a), (Dan et al., 2024), (Yu et al., 2024b) and (Hu et al., 2023)

Table 22
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	Fully connected gated graph architecture (FC-GAGA) (Zeng et al., 2022)	(Guo et al., 2023b), (Chen et al., 2025) and (Bikram et al., 2024)
	Gated attention networks for learning on large and spatiotemporal graphs (GaAN) (Zhang et al., 2018)	(Wang et al., 2020) and (Park et al., 2020)
	Graph convolutional network (GCN)	(Zhang et al., 2022a), (Jiang et al., 2022), (Sánchez-Rada et al., 2024), (He & Shin, 2020b) and (Tang et al., 2022)
	GeoMAN (Liang et al., 2018)	(Li et al., 2022a) and (Cao et al., 2022)
	Graph multi-attention network (GMAN) (Zheng et al., 2020)	(Li et al., 2023b), (Li et al., 2023d), (Lablack & Shen, 2023), (Guo et al., 2023b), (Khaled et al., 2022), (Bui et al., 2022), (Chen et al., 2025), (Jakhmola et al., 2024), (Zang et al., 2024), (Bikram et al., 2024), (Kwak et al., 2024), (Li et al., 2024a), (Wang et al., 2024e), (Shao et al., 2022b), (Jiang et al., 2024b), (Han et al., 2021), (Shao et al., 2022c), (Zhu et al., 2023), (Zou et al., 2024a), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Li et al., 2021d), (Chen et al., 2020a), (Li et al., 2023c), (Yu et al., 2024b), (Ma et al., 2023), (Hu et al., 2023) and (Park et al., 2020)
	Discrete graph structure learning for time series (GTS) (Shang et al., 2021)	(Huo et al., 2024), (Li et al., 2024g), (Shao et al., 2022b), (Jiang et al., 2024b), (Jin et al., 2023d), (Zhu et al., 2023), (Wang et al., 2023e) and (Ma et al., 2023)
	Graph WaveNet (GWN) (Wu et al., 2019)	(Lu et al., 2022a), (Li et al., 2023b), (Jin et al., 2023a), (Li et al., 2023d), (Lablack & Shen, 2023), (Kumar et al., 2023), (Yang et al., 2023b), (Guo et al., 2023b), (Gu et al., 2023), (Khaled et al., 2022), (Lu et al., 2022c), (Bui et al., 2022), (Li et al., 2024c), (Chen et al., 2025), (Jakhmola et al., 2024), (Huo et al., 2024), (Zang et al., 2024), (Wei et al., 2024b), (Kwak et al., 2024), (Singh et al., 2024), (Li et al., 2024g), (Wu et al., 2024c), (Zhao et al., 2024), (Shin & Yoon, 2024), (Li et al., 2024a), (Han et al., 2024b), (Fang et al., 2024), (Kong et al., 2024a), (Shao et al., 2022b), (Jiang et al., 2024b), (Han et al., 2021), (Zhang et al., 2024f), (Jin et al., 2023d), (Fang et al., 2023a), (Shao et al., 2022c), (Zhu et al., 2023), (Fang et al., 2021), (Gupta et al., 2023), (Liu et al., 2022a), (Hu et al., 2024b), (Gao et al., 2024a), (Zou et al., 2024a), (Wu et al., 2023), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Wang et al., 2023e), (Zhou et al., 2024b), (Li et al., 2021d), (Chen et al., 2020a), (Li et al., 2023c), (Yu et al., 2024b), (Ma et al., 2023), (Hu et al., 2023), (Park et al., 2020) and (Ou et al., 2020)
	Hierarchical graph convolution network (HGCN) (Guo et al., 2021)	(Wang et al., 2024d) and (Ma et al., 2023)
	Long short-term graph convolutional networks (LSGCN) (Huang et al., 2021a)	(Li et al., 2023e), (Singh et al., 2024), (Feng et al., 2024c), (Fang et al., 2024) and (Fang et al., 2023a)
	Multi-graph convolutional networks (MGCN) (Chai et al., 2018)	(Liang et al., 2023) and (He & Shin, 2020a)
	Multi-range attentive bicomponent graph convolutional network (MRA-BGCN) (Chen et al., 2020c)	(Li et al., 2023d), (Guo et al., 2023b), (Chen et al., 2025) and (Li et al., 2021d)
	Multivariate time series forecasting with graph neural network (MTGNN) (Wu et al., 2020c)	(Li et al., 2023b), (Li et al., 2023d), (Lablack & Shen, 2023), (Kumar et al., 2023), (Guo et al., 2023b), (Gu et al., 2023), (Khaled et al., 2022), (Lu et al., 2022c), (Bui et al., 2022), (Li et al., 2024c), (Chen et al., 2025), (Huo et al., 2024), (Zang et al., 2024), (Li et al., 2024a), (Liao et al., 2024c), (Shao et al., 2022b), (Jiang et al., 2024b), (Han et al., 2021), (Shao et al., 2022c), (Zhu et al., 2023), (Zou et al., 2024a), (Li et al., 2022b), (Li et al., 2021d), (Chen et al., 2020a), (Li et al., 2023c) and (Ma et al., 2023)
	Multi-view graph convolutional network (MVGCN) (Sun et al., 2019)	(Xia et al., 2021b) and (Li et al., 2022a)
	Propagation delay-aware dynamic long-range transformer (PDFormer) (Jiang et al., 2023a)	(Li et al., 2024g), (Zhang et al., 2024f), (Gao et al., 2024a) and (Yu et al., 2024b)
	a Spatio-temporal adaptive embedding transformer (STAEformer) (Liu et al., 2023a)	(Zhang et al., 2024f) and (Dan et al., 2024)
	Spectral temporal graph neural network for multivariate time-series forecasting (StemGNN) (Cao et al., 2020)	(Li et al., 2024c), (Zang et al., 2024), (Wang et al., 2023e) and (Hajisafi et al., 2023)
	STGNN enhanced by a scalable time series Pre-training model (STEP) (Shao et al., 2022b)	(Jiang et al., 2024b), (Hu et al., 2024b) and (Wang et al., 2023e)
	Spatial-temporal fusion graph neural network (STFGNN) (Li & Zhu, 2021)	(Li et al., 2022c), (Jin et al., 2023a), (Yang et al., 2023b), (Gu et al., 2023), (Zhao et al., 2023), (Gu & Deng, 2022), (Li et al., 2024c), (Zhao et al., 2024), (Liao et al., 2024c), (Fang et al., 2024), (Fang et al., 2023a), (Lan et al., 2022), (Liu et al., 2022a), (Fan et al., 2023), (Gao et al., 2024a), (Li et al., 2022b), (Chen et al., 2020a), (Li et al., 2023c) and (Hu et al., 2023)
	Spatial-temporal graph to sequence model (STG2Seq) (Bai et al., 2019)	(Li et al., 2023e), (Wei et al., 2024b), (Liu et al., 2022a), (Fan et al., 2023), (Wu et al., 2023) and (Zhou et al., 2024b)

Table 22
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Spatio-temporal graph convolutional network (STGCN) (Yu et al., 2018)	(Lu et al., 2022a), (Xia et al., 2021b), (Li et al., 2022a), (Li et al., 2023e), (Li et al., 2023b), (Liu et al., 2023b), (Jin et al., 2023a), (Li et al., 2023d), (Lablack & Shen, 2023), (Kumar et al., 2023), (Yang et al., 2023b), (Guo et al., 2023b), (Gu et al., 2023), (Zhang & Guo, 2022), (Zhao et al., 2022a), (Khaled et al., 2022), (Lu et al., 2022c), (Chen et al., 2020b), (Bui et al., 2022), (Cai et al., 2022), (Gu & Deng, 2022), (Diao et al., 2023a), (Cao et al., 2022), (Li et al., 2024c), (Chen et al., 2025), (Jakhmola et al., 2024), (Huo et al., 2024), (Wang et al., 2024d), (Zang et al., 2024), (Wei et al., 2024b), (Peng et al., 2024), (Li et al., 2024g), (Zhao et al., 2024), (Wei et al., 2024a), (Wang et al., 2024a), (Wu et al., 2024b), (Li et al., 2024a), (Liao et al., 2024c), (Wang et al., 2024e), (Fang et al., 2024), (Kong et al., 2024a), (Jiang et al., 2024b), (Fang et al., 2023a), (Lan et al., 2022), (Fang et al., 2021), (Gupta et al., 2023), (Liu et al., 2022a), (Bai et al., 2020), (Fan et al., 2023), (Gao et al., 2024a), (Zou et al., 2024a), (Feng & Tassiulas, 2022), (Li et al., 2022b), (Wang et al., 2023e), (Li et al., 2021d), (Tang et al., 2022), (Chen et al., 2020a), (Li et al., 2023c), (Yu et al., 2024b), (Ma et al., 2023), (Zhang et al., 2020c), (Hu et al., 2023), (Lu et al., 2020), (Park et al., 2020), (Ou et al., 2020) and (Wölker et al., 2023)
Spatio-temporal graph few shot learning (ST-GFSL) (Lu et al., 2022b)	(Jin et al., 2023d) and (Hu et al., 2024b)
Spatial temporal graph neural network (STGNN) (Wang et al., 2020)	(Xia et al., 2021b), (Liu et al., 2023c) and (Wang et al., 2020)
Spatial-temporal graph ODE networks (STGODE) (Fang et al., 2021)	(Li et al., 2023e), (Jin et al., 2023a), (Gu et al., 2023), (Zhao et al., 2023), (Li et al., 2024c), (Wei et al., 2024b), (Han et al., 2024b), (Fang et al., 2024), (Fang et al., 2023a), (Lan et al., 2022), (Gupta et al., 2023), (Fan et al., 2023), (Gao et al., 2024a), (Wu et al., 2023), (Li et al., 2022b), (Tang et al., 2022) and (Chen et al., 2020a)
Spatio-temporal graph attention network (ST-GRAT) (Park et al., 2020)	(Guo et al., 2023b) and (Li et al., 2024a)
Deep-meta-learning based model (ST-MetaNet) (Pan et al., 2019)	(Li et al., 2022a), (Li et al., 2023b), (Li et al., 2023d), (Guo et al., 2023b), (Chen et al., 2025), (Wang et al., 2024e), (Zhu et al., 2023), (Li et al., 2022b), (Li et al., 2021d), (Chen et al., 2020a), (Li et al., 2023c) and (Zhang et al., 2020c)
Spatiotemporal multi-graph convolution network (ST-MGCN) (Geng et al., 2019)	(Wang et al., 2024e) and (Zhang et al., 2020c)
Spatio-temporal synchronous graph convolutional network (STSGCN) (Song et al., 2020a)	(Li et al., 2022c), (Li et al., 2023e), (Li et al., 2023b), (Jin et al., 2023a), (Yang et al., 2023b), (Gu et al., 2023), (Zhao et al., 2023), (Gu & Deng, 2022), (Diao et al., 2023a), (Li et al., 2024c), (Jakhmola et al., 2024), (Wei et al., 2024b), (Zhao et al., 2024), (Shin & Yoon, 2024), (Wang et al., 2024a), (Wu et al., 2024b), (Fang et al., 2024), (Kong et al., 2024a), (Shao et al., 2022b), (Jiang et al., 2024b), (Fang et al., 2023a), (Shao et al., 2022c), (Zhu et al., 2023), (Lan et al., 2022), (Fang et al., 2021), (Liu et al., 2022a), (Bai et al., 2020), (Fan et al., 2023), (Gao et al., 2024a), (Li et al., 2022b), (Chen et al., 2020a), (Li et al., 2023c), (Yu et al., 2024b) and (Hu et al., 2023)
Temporal graph convolutional network (T-GCN) (Zhao et al., 2020b)	(Liu et al., 2023c), (Kumar et al., 2023), (Zhao et al., 2022a), (Wang et al., 2024d), (Li et al., 2024g), (Wang et al., 2020), (Zou et al., 2024a), (Wu et al., 2023), (Tang et al., 2022), (Ramhormozi et al., 2022) and (Ma et al., 2023)
Time zigzags at graph convolutional networks for time series forecasting (Z-GCNETs) (Chen et al., 2021)	(Zhao et al., 2023), (Wei et al., 2024b), (Shin & Yoon, 2024), (Lan et al., 2022), (Fan et al., 2023) and (Hu et al., 2023)

et al., 2019), all developed specifically for the traffic forecasting problem.

The STGCN model proposed by Yu et al. (2018) consists of two spatio-temporal convolutional blocks (with two temporal gated convolutional layers, one spatial graph convolutional layer in the middle, and residual connections) and a fully-connected output layer in the end. In its original implementation, it processes graphs a with weighted adjacency matrix based on spatial distance between sensors in the road network. The source code for the STGCN model is available at https://github.com/VeritasYin/STGCN_IJCAI-18. The DCRNN model proposed by Li et al. (2018) aims to capture the spatial dependency by using bidirectional random walks on the graph (whose adjacency matrix is based on node proximity), and to capture the temporal dependencies by using an encoder-decoder architecture with scheduled sampling. The code can be accessed at https://github.com/liyaguang/DCRNN. The GWN model was introduced by Wu et al. (2019) as a novel approach to spatio-temporal forecasting, particularly in traffic tasks. It is known for its ability to learn an adaptive dependency matrix from node embeddings. The model combines graph convolutional and temporal convolutional layers to effectively capture spatio-temporal dependencies. The source code is available at https://github.com/nnzhan/Graph-WaveNet. The ASTGCN model proposed by Guo et al. (2019) models at once recent, daily-periodic and weekly-periodic dependencies as three independent components, with a spatio-temporal attention mechanism for capturing the dynamic spatio-temporal correlations and a spatio-temporal convolution which simultaneously employs graph convolutions to capture the spatial patterns. The source code for the ASTGCN model is available at https://github.com/Davidham3/ASTGCN-2019-mxnet. For a more comprehensive list of source codes for the most dated benchmark GNN models in the traffic domain see Jiang and Luo (2022).

5.5.5. Results

In all papers mentioned, the authors claim that the proposed GNN-based models are able to outperform the benchmarks. However, there are a limited but interesting number of situations in which some simple statistical and mathematical models demonstrate comparable accuracy, as it can be observed in Tables 23 and 24.

For the comparison and evaluation of these models, the most commonly used error metrics are MAE, RMSE, and MAPE. A few papers in addition use further metrics such as the coefficient of determination R^2. However, despite the use of the same metrics and the availability of widely used datasets, comparison among these models is not triv-

ial, because different papers often focus on different time windows of a dataset.

In Table 23 it is shown the accuracy of the different models applied to the METR-LA dataset, with a 5-minute granularity from 1st March 2012 to 30th June 2012 for 15, 30 and 60 minute time horizons, expressed in terms of MAE, MAPE and RMSE.

Clearly, the results on the METR-LA dataset are not uniform, and the best performing models vary depending on the metric and the time horizon. However, the multichannel fusion graph neural network (MCFGNN) (Chen & Xie, 2022) from the "Generic" group consistently exhibits low errors across different time horizons. The MCFGNN model is composed of three main components: a graph construction layer, a graph convolution layer, and a temporal convolution layer. The input data are first processed by the graph construction layer, which incorporates three channels to capture meta-features, time-varying patterns, and globally stabilized graphs. Spatial and temporal convolutions are then applied in pairs to capture spatio-temporal dependencies in the data. To mitigate the issue of vanishing gradients, residual connections are added to each spatio-temporal block.

Table 24 displays the accuracy of various models on the PEMS-BAY dataset with a 5-minute granularity and data spanning from 1st January 2017 to 30th June 2017 for 15, 30 and 60 minute time horizons, with results expressed in terms of MAE, MAPE and RMSE.

The results on the PEMS-BAY dataset vary depending on the metrics and the time horizon. The most accurate models are the adaptive multigraph convolutional networks (AMGCN) (Li et al., 2024a), and the spatio-temporal GNN enhanced by a scalable time series pre-training model (STEP) (Shao et al., 2022b). The AMGCN model includes a graph fusion block, an adaptive graph generator block, a stack of spatio-temporal convolution blocks, and an output module. The graph fusion block integrates information from five pre-defined graph structures, based on spatial distance, reachability, correlation, and distributions. Then, an independent adaptive graph generator learns an evolving graph structure to complement the pre-defined graph. Spatio-temporal features are finally extracted through a stack of graph convolutional modules with residual connections, and a time-mixing strategy. The STEP model was proposed by Shao et a. in 2021 as a framework to enhance spatio-temporal GNNs through a pre-training approach. Specifically, the pre-training model is designed to learn temporal patterns from long-term historical time series data and generate segment-level representations. These representations, which capture rich contextual information, are then integrated into a spatio-temporal GNN to improve its performance on short-term forecasting tasks. To demonstrate the effectiveness of the framework, the authors use Graph WaveNet as a representative backbone model within STEP.

Other models that, overall, achieve good results are the multi view spatial-temporal graph neural network (MVST-GNN) (Li et al., 2023d), and the temporal decomposition based dynamic multi granularity graph neural network (TD2MG2NN) (Zang et al., 2024). The MVST-GNN model includes a multi-view temporal transformer module and a multi-view graph convolution module. The multi-view temporal transformer module is designed to capture dynamic temporal features from recent, daily, and weekly patterns using self-attention and a fusion module. Then, the graph convolution module operates on a self-learned adjacency matrix and passes its output through two fully connected linear layers to generate the final forecast. The TD2MG2NN model, instead, was introduced for evaluating the resilience of road networks in real time during heavy rain events. The process starts by decomposing the time series into seasonal and trend components. These components are processed individually through a season-temporal encoder layer with temporal convolutions, and a trend-temporal encoder layer with regression, respectively. The model then learns two feature matrices, one for daily and one for weekly patterns, which are fed into a dynamic multi-granularity graph convolution module. This module processes the feature matrices in parallel, and then passes them through a spatial decoder layer to produce the final output.

As for the other PeMS datasets (PeMS03, PeMS04, PeMS07 and PeMS08), the results are largely consistent with an indication that the periodicity aware spatial-temporal adaptive hypergraph neural network (PAHNN) (Zhao et al., 2024) is the most accurate model, as shown in Tables 25–28. Table 25 reports the accuracy of the different models applied to the PeMS03 dataset, which includes data from 1st September 2018 to 30th November 2018 at a 5-minute granularity for a 60-minute time horizon, with results given in terms of MAE, MAPE and RMSE.

In Table 26 is shown the accuracy of the different models on the PeMS04 dataset with a 5-minute granularity and data from 1st January 2018 to 28th February 2018 a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE.

The MAE, MAPE and RMSE of the different models on the PeMS07 dataset, with data from 1st May 2017 to 31st August 2017, a 5-minute granularity and a 60-minute time horizon, are presented in Table 27.

Finally, Table 28 displays the accuracy of the various models on the PeMS08 dataset with a 5-minute granularity and data spanning from 1st July 2016 to 31st August 2016 for a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE.

As stated above, the results almost consistently indicate that the periodicity aware spatial-temporal adaptive hypergraph neural network (PAHNN) proposed by Zhao et al. (2024) is the most accurate model. The PAHNN model includes a temporal multi-periodic to time dependencies and periodic features of traffic time series, and a spatial adaptive hypergraph neural network to capture higher-order correlations among nodes.

5.6. Predictive monitoring

The theme of predictive monitoring is related to sensor-based monitoring of processes, which has become essential in modern industry. The evolution of monitoring systems is concomitant with the rapid growth of the Internet of Things (IoT), which aims at a smarter management across various applications (Li et al., 2022d). Hence, in this context, multi-sensor systems can be used to detect anomalies in complex scenarios and to monitor the overall status of a system. In the specific, predictive monitoring is a task that involves the continuous observation and analysis of a system in order to forecast its future states and verify whether the predicted outcomes meet certain standards. The predictive monitoring task is important because it can significantly improve efficiency, reliability, and cost of industrial operations. Related data-based approaches include techniques such as anomaly detection, fault diagnosis, and estimation of the equipment's remaining useful life.

Despite the specificity of the field, 40 out of 366 papers address the topic of predictive monitoring. This includes anomaly detection (Buchhorn et al., 2023; Guo et al., 2024; Han & Woo, 2022; He et al., 2024b; Hojjati et al., 2023; Lee et al., 2023; Li et al., 2022d, 2023g, 2024e; Liao et al., 2024b; Liu et al., 2024e; Malarkkan et al., 2024; Zheng et al., 2024a,b), fault diagnosis (Kovalenko et al., 2024; Lei et al., 2023; Li et al., 2021a; Ning et al., 2023; Van Gompel et al., 2023; Wang et al., 2024b,c,f; Yuan et al., 2023; Zhang et al., 2024a, 2023f) and RUL estimation (Chen & Zeng, 2023; Kong et al., 2024b, 2022; Mylonas & Chatzi, 2021; Wang et al., 2023b,i; Wei & Wu, 2023; Yang et al., 2022; Zhang et al., 2024d). The use of GNNs in these analyses is justified by the necessity of using a model capable of capturing the spatio-temporal correlations among the many sensors present in the system.

5.6.1. Overview

As said, predictive monitoring is a research field which focuses on several techniques, such as anomaly detection, fault diagnosis and remaining useful life estimation. Anomaly detection is a technique that aims to identify abnormal data that are not due to random deviations from some regular pattern, but are generated by a different underlying mechanism (Hawkins, 1980). It is a prerequisite part of fault diagnosis (Jiao et al., 2018). Fault diagnosis is the process of determining whether a fault has occurred in a machine, including the identification of the

Table 23
Comparison of the average accuracy of the different models on the METR-LA dataset for 15, 30 and 60 minute time horizons, expressed in terms of MAE, MAPE and RMSE. The results of the models marked with ⋆ are taken from papers in the "Generic" group. The smallest errors are underlined. Numbers from the original papers.

Time horizon	15 min			30 min			60 min		
Metrics	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE
AGCRN	2.87	7.70	5.58	3.23	9.00	6.58	3.62	10.38	7.51
AGP-GNN (Guo et al., 2023b)	2.71	7.21	5.25	3.04	8.15	6.20	3.41	9.70	7.20
AMGCN (Li et al., 2024a)	2.52	6.13	4.48	2.97	7.70	5.35	3.38	8.93	6.21
ARIMA	3.99	9.60	8.12	5.15	12.70	10.45	6.90	17.40	13.23
ASTGCN	4.86	9.21	9.27	5.43	10.13	10.61	6.51	11.64	12.52
ASTGNN	2.66	6.96	5.09	3.06	8.47	6.26	3.52	9.56	7.21
AutoSTG	2.70	-	5.16	3.06	-	6.17	3.47	-	7.27
AutoSTS (Li et al., 2022b)	2.57	6.55	4.93	2.89	7.85	5.87	3.28	9.43	6.86
CASTGNN (Wang et al., 2024a)	2.88	6.67	6.44	3.25	7.91	7.56	3.70	9.76	8.92
D^2STGNN (Shao et al., 2022c)	2.56	6.48	4.88	2.90	7.78	5.89	3.35	9.40	7.03
DCRNN	2.77	7.30	5.38	3.15	8.80	6.45	3.60	10.50	7.60
DetectorNet (Li et al., 2021d)	-	-	-	3.06	8.12	6.08	3.40	9.60	6.98
DGCRN (Li et al., 2023b)	2.62	6.63	5.01	2.99	8.02	6.05	3.44	9.73	7.19
DMSTGCN	2.85	7.54	5.54	3.26	9.19	6.56	3.72	10.96	7.55
DST-GCNN (Chen et al., 2020b)	2.68	7.20	5.35	3.01	8.50	6.23	3.41	10.30	7.47
DualGraph (Wei et al., 2024a)	2.62	7.10	5.36	2.83	7.90	5.89	3.15	9.10	6.67
DyGCN-LSTM (Kumar et al., 2023)	2.64	6.35	4.64	3.24	8.04	5.24	3.53	9.30	6.53
DyHSL	2.58	6.47	4.98	2.95	8.05	6.13	3.41	9.41	7.03
FC-GAGA	2.75	7.25	5.34	3.10	8.57	6.30	3.51	10.14	7.31
FNN	3.99	9.90	7.94	4.23	12.90	8.17	4.49	14.00	8.69
GA-LSTM (Zhang & Guo, 2022)	2.30	7.01	4.97	2.98	8.50	6.00	3.55	9.97	7.23
GaAN	2.71	6.99	5.24	3.12	8.56	6.36	3.64	10.62	7.65
GGRU	2.71	6.99	5.24	3.12	8.56	6.36	3.64	10.62	7.65
GL-STGTN (Li et al., 2024g)	2.61	6.94	5.08	2.96	8.23	5.97	3.37	9.81	6.99
GMAN	2.77	7.25	5.48	3.07	8.35	6.34	3.40	9.72	7.22
GTS⋆ (Shang et al., 2021)	2.64	6.80	4.95	3.01	8.20	5.85	3.41	9.90	6.74
GWN	2.69	6.90	5.15	3.07	8.37	6.22	3.53	10.01	7.37
HA	4.16	13.00	7.80	4.16	13.00	7.80	4.16	13.00	7.80
HighResNet	2.68	6.88	5.10	3.03	8.34	6.11	3.47	10.24	7.27
LSTM	3.44	9.60	6.30	3.77	10.90	7.23	4.37	13.20	8.69
MCFGNN⋆ (Chen & Xie, 2022)	2.31	5.86	5.29	2.66	6.89	6.27	3.05	7.65	7.20
MRA-BGCN	2.67	6.80	5.12	3.06	8.30	6.17	3.49	10.00	7.30
MTGNN⋆ (Wu et al., 2020c)	2.69	6.86	5.18	3.05	8.19	6.17	3.49	9.87	7.23
MTGODE⋆ (Jin et al., 2023c)	2.66	6.87	5.10	3.00	8.19	6.05	3.39	9.80	7.05
MVST-GNN (Li et al., 2023d)	2.70	5.19	6.97	3.06	8.12	6.08	3.40	9.60	6.98
PAHNN (Zhao et al., 2024)	2.51	6.34	4.82	2.87	7.63	5.73	3.25	9.32	6.67
PDFormer	2.83	7.77	5.45	3.20	9.19	6.46	3.62	10.91	7.47
PGCN (Shin & Yoon, 2024)	2.70	6.98	5.16	3.08	8.38	6.22	3.54	9.94	7.36
SAGDFN (Jiang et al., 2024b)	2.56	6.50	5.00	2.94	7.90	6.05	3.37	9.50	7.17
SDGCN	2.76	7.16	5.38	3.15	8.53	6.46	3.61	9.87	7.43
SLCNN	2.53	6.70	5.18	2.88	8.00	6.15	3.30	9.70	7.20
SNAS4MTF (Chen et al., 2025)	2.68	6.90	5.16	3.03	8.25	6.12	3.43	9.82	7.15
STAG-GCN (Lu et al., 2022a)	2.67	7.00	5.23	3.07	8.26	6.15	3.50	9.93	7.24
STAEFormer	2.65	6.85	5.11	2.97	8.13	6.00	3.34	9.70	7.02
STEP (Shao et al., 2022b)	2.61	6.60	4.98	2.96	7.96	5.97	3.37	9.61	6.99
STID	2.82	7.75	5.53	3.19	9.39	6.57	3.55	10.95	7.55
STFGNN⋆	2.57	6.51	4.73	2.83	7.46	5.46	3.18	8.81	6.40
STGCN	2.88	7.62	5.74	3.47	9.57	7.24	4.59	12.70	9.40
STGODE⋆	3.47	8.76	6.76	4.36	11.14	8.47	5.50	14.32	10.33
STG-NCDE⋆	3.77	8.54	9.47	4.84	10.63	12.04	6.35	13.49	14.94
STGRAT	2.60	6.61	5.07	3.01	8.15	6.21	3.49	10.01	7.42
ST-MetaNet	2.69	6.91	5.17	3.10	8.57	6.28	3.59	10.63	7.52
STSD (Zhu et al., 2023)	2.60	6.55	4.96	2.96	7.93	5.98	3.37	9.51	7.03
STSGCN	3.31	8.06	7.62	4.13	10.29	9.77	5.06	12.91	11.66
SVR	3.99	9.30	8.45	5.05	12.10	10.87	6.72	16.70	13.76
TF-GAN (Khaled et al., 2022)	2.63	6.55	4.94	3.06	8.36	6.20	3.32	9.48	7.11
T-GCN	3.03	7.81	5.26	3.52	9.45	6.12	4.30	11.80	7.31
TGC-GRU	5.25	12.45	8.56	5.99	14.18	10.37	7.32	17.11	13.47
VAR	4.42	10.20	7.89	5.41	12.70	9.13	6.52	15.80	10.11
TimesNet	2.78	7.52	5.49	3.36	9.43	6.41	4.52	11.37	9.66
TwoResNet (Kwak et al., 2024)	2.65	6.78	5.08	3.01	8.14	6.07	3.39	9.71	7.08
WaveNet	2.99	8.04	5.89	3.59	10.25	7.28	4.45	13.62	8.93
Z-GCNETs	3.23	7.87	7.48	3.93	9.75	9.40	4.83	12.04	11.57

Table 24
Comparison of the average accuracy of the different models on the PEMS-BAY dataset for 15, 30 and 60 minute time horizons, expressed in terms of MAE, MAPE and RMSE. The smallest errors are underlined. Numbers from the original papers.

Time horizon	15 min			30 min			60 min		
Metrics	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE
AGCRN	1.37	2.94	2.87	1.69	3.87	3.85	1.96	4.64	4.54
AGP-GNN (Guo et al., 2023b)	1.33	2.79	2.86	1.61	3.66	3.67	1.86	4.30	4.34
AMGCN (Li et al., 2024a)	1.22	2.63	2.34	1.53	3.55	3.13	1.93	4.66	3.95
ARIMA	1.62	3.50	3.30	2.33	5.40	4.76	3.38	8.30	6.50
ASTGCN	1.52	3.22	3.13	2.01	4.48	4.27	2.61	6.00	5.42
ASTGNN	1.34	3.84	2.75	1.65	3.72	3.74	1.94	4.59	4.51
AutoSTG	1.33	2.79	2.78	1.63	3.66	3.62	1.91	4.57	4.42
AutoSTS (Li et al., 2022b)	1.28	2.66	2.63	1.57	3.54	3.50	1.83	4.41	4.27
D^2STGNN (Shao et al., 2022c)	1.24	2.58	2.60	1.55	3.49	3.52	1.85	4.37	4.30
DCRNN	1.38	2.90	2.95	1.74	3.90	3.97	2.07	4.90	4.74
DetectorNet (Li et al., 2021d)	-	-	-	1.57	3.56	3.54	1.80	4.19	4.26
DGCRN (Li et al., 2023b)	1.28	2.66	2.69	1.59	3.55	3.63	1.89	4.43	4.42
DMSTG	-	-	-	-	-	-	1.91	4.51	4.43
DMSTGCN	1.33	2.80	2.83	1.67	3.81	3.79	1.99	4.78	4.54
DSTCGCN	-	-	-	-	-	-	1.95	4.66	4.51
DyHSL	1.30	2.73	2.71	1.60	3.57	3.67	1.95	4.62	4.53
FC-GAGA	1.36	2.87	2.86	1.68	3.80	3.80	1.97	4.67	4.52
FNN	2.20	5.19	4.42	2.30	5.43	4.63	2.46	5.89	4.98
GL-STGTN (Li et al., 2024g)	1.26	2.79	2.73	1.55	3.63	3.58	1.80	4.38	4.30
GMAN	1.34	2.81	2.82	1.62	3.62	3.72	1.86	4.31	4.32
GSLNN (Huo et al., 2024)	1.29	2.71	2.66	1.64	3.67	3.74	1.93	4.51	4.46
GTS* (Shang et al., 2021)	1.32	2.80	2.62	1.64	3.60	3.41	1.91	4.40	3.97
GWN	1.30	2.73	2.74	1.63	3.67	3.70	1.95	4.63	4.52
Informer*	2.30	5.02	4.21	2.40	5.32	4.49	2.55	5.73	4.85
LDS*	1.33	2.80	2.81	1.67	3.80	3.80	1.99	4.80	4.59
HA	1.89	4.16	4.30	2.50	5.62	5.82	3.31	7.65	7.54
LSTM	2.05	4.80	4.19	2.20	5.20	4.55	2.37	5.70	4.96
LSVR	1.85	3.80	3.59	2.48	5.50	5.18	3.28	8.00	7.08
HighResNet	1.31	2.74	2.75	1.64	3.68	3.75	1.95	4.61	4.56
MegaCRN	1.28	2.67	2.72	1.60	3.57	3.68	1.88	4.41	4.42
MRA-BGCN	1.29	2.90	2.72	1.61	3.80	3.67	1.91	4.60	4.46
MTGNN* (Wu et al., 2020c)	1.32	2.77	2.79	1.65	3.69	3.74	1.94	4.53	4.49
MTGODE* (Jin et al., 2023c)	1.29	2.72	2.73	1.61	3.61	3.66	1.88	4.39	4.31
MVST-GNN (Li et al., 2023d)	1.30	2.73	2.74	1.57	3.56	3.54	1.80	4.19	4.26
PAHNN (Zhao et al., 2024)	1.27	2.60	2.65	1.52	3.48	3.54	1.83	4.35	4.27
PDFormer	1.32	2.78	2.83	1.64	3.71	3.79	1.91	4.51	4.43
PGCN (Shin & Yoon, 2024)	1.30	2.72	2.73	1.62	3.63	3.67	1.92	4.45	4.45
RGSL	-	-	-	-	-	-	2.03	4.77	4.64
RST-LTG (Li et al., 2024c)	-	-	-	-	-	-	1.88	4.32	4.31
SDGCN	1.35	2.89	2.88	1.69	3.87	3.91	1.99	4.69	4.59
SLCNN	1.44	3.00	2.90	1.72	3.90	3.81	2.03	4.80	4.53
SNAS4MTF (Chen et al., 2025)	1.30	2.72	2.77	1.61	3.63	3.68	1.89	4.44	4.36
STAEFormer	1.31	2.76	2.78	1.62	3.62	3.68	1.88	4.41	4.34
StemGNN	1.44	3.08	3.12	1.93	4.54	4.38	2.57	6.55	5.88
STEP (Shao et al., 2022b)	1.26	2.59	2.73	1.55	3.43	3.58	1.79	4.18	4.20
STID	1.30	2.73	2.81	1.62	3.68	3.72	1.89	4.47	4.40
STFGNN	1.42	2.92	2.97	1.67	3.92	3.94	1.98	4.83	4.74
STGCN	1.36	2.90	2.96	1.81	4.17	4.27	2.49	5.79	5.69
STG-NCDE*	1.38	2.91	2.93	1.71	3.91	3.84	2.03	4.82	4.58
STGODE*	1.43	2.99	2.88	1.84	3.84	3.90	2.30	4.61	4.89
STGRAT (Park et al., 2020)	1.29	2.67	2.71	1.61	3.63	3.69	1.95	4.64	4.54
ST-MetaNet	1.36	2.82	2.90	1.76	4.00	4.02	2.20	5.45	5.06
ST-Norm	1.34	2.82	2.88	1.67	3.75	3.83	1.96	4.62	4.52
STSD (Zhu et al., 2023)	1.28	2.64	2.69	1.60	3.54	3.63	1.88	4.35	4.36
STSGCN	1.44	3.04	3.01	1.83	4.17	4.18	2.26	5.40	5.21
SVR	1.85	3.80	3.59	2.48	5.50	5.18	3.28	8.00	7.08
TD2MG2NN (Zang et al., 2024)	1.25	2.62	2.64	1.55	3.47	3.50	1.85	4.28	4.22
TGC-GRU	2.34	5.08	4.30	2.44	5.40	4.64	2.57	5.78	5.01
T-GCN	1.50	3.14	2.83	1.73	3.76	3.40	2.18	4.94	4.35
TimesNet	1.32	2.94	2.72	1.76	3.74	4.16	2.18	4.84	5.20
TPGNN* (Liu et al., 2022d)	1.26	2.56	2.64	1.65	3.47	3.65	2.05	4.40	4.58
TwoResNet (Kwak et al., 2024)	1.30	2.70	2.73	1.61	3.59	3.69	1.89	4.40	4.41
VAR	1.74	3.60	3.16	2.32	5.00	4.25	2.93	6.50	5.44
WaveNet	1.39	2.91	3.01	1.83	4.16	4.21	2.35	5.87	5.43
Z-GCNETs	1.36	2.88	2.86	1.68	3.79	3.78	1.98	4.60	4.53

time, location, type, and severity of the fault. It is usually considered to be a classification problem. As for remaining useful life (RUL) estimation, it aims to determine how long a machine will operate before it needs to be repaired or replaced, and it is useful for scheduling maintenance interventions.

The selected papers implement these three techniques, with anomaly detection being less studied than the other two. The main applications developed are industrial (e.g., bearings fault diagnosis in Li et al., 2021a; Mylonas & Chatzi, 2021; Ning et al., 2023; Yang et al., 2022; Yuan et al., 2023) and mechanical (e.g, engines RUL estimation in Chen &

Table 25
Comparison of the average accuracy of the different models on the PeMS03 dataset for a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE. The results of the models marked with * are taken from papers in the "Generic" group. The smallest errors are underlined. Numbers from the original papers.

Time horizon	60 min		
Metrics	MAE	MAPE	RMSE
AdaSTNet	15.49	14.84	27.57
AGCRN	15.98	15.23	28.25
ARIMA	35.41	33.78	47.59
ASTGCN	17.69	19.40	29.66
ASTGNN	14.78	14.79	25.00
Auto-DSTSGN (Jin et al., 2023a)	14.59	14.22	25.17
AutoSTG	16.27	16.10	27.63
AutoSTS (Li et al., 2022b)	14.61	14.18	24.71
DCGCN (Gu et al., 2023)	15.29	-	25.98
DCRNN	18.18	18.91	30.31
DeepGLO*	17.25	19.27	23.25
DeepState*	15.59	18.69	20.21
DSTAGNN (Lan et al., 2022)	15.57	14.68	27.21
DyHSL	15.49	14.38	27.06
FourierGNN	17.27	15.88	27.20
Gboot (Gao et al., 2024a)	15.43	14.51	26.42
GMAN	15.52	15.19	26.53
GMSDR (Liu et al., 2022a)	15.78	15.33	26.82
GWN	19.85	19.31	32.94
HA	31.58	33.78	52.39
LSGCN	17.94	-	29.85
LSTM	21.33	23.33	35.11
LSTNet*	19.07	17.73	29.67
N-BEATS*	18.45	18.35	31.23
PAHNN (Zhao et al., 2024)	14.02	13.19	23.67
PDFormer	21.82	21.47	36.75
PYNet (Hu et al., 2023)	14.94	14.94	25.27
SFM*	17.67	18.33	30.01
SPGCL	23.31	21.88	37.37
STAGCN (Gu & Deng, 2022)	15.40	14.48	26.23
STCGNN (Yang et al., 2023b)	15.81	14.59	27.23
StemGNN*	14.32	16.24	21.64
STFGCN	16.77	16.30	28.34
STGBN (Fan et al., 2023)	15.22	14.78	27.09
STGCN	17.49	17.15	30.12
STG2SEC	19.03	21.55	29.73
STGODE	16.53	16.68	27.79
STSGCN	17.48	16.78	29.21
STWave (Fang et al., 2023a)	14.93	15.05	26.50
STWave+ (Fang et al., 2024)	14.71	14.88	26.31
SVR	21.97	21.51	35.29
TAMP-S2GCNets* (Chen et al., 2022e)	13.91	13.40	23.77
TCN	19.32	19.93	33.55
TimesNet	16.41	15.17	26.72
VAR	23.65	24.51	38.26
W-DSTAGNN (Jakhmola et al., 2024)	15.31	14.49	26.59
Z-GCNETs	14.20	13.88	25.29

Zeng, 2023; Kong et al., 2024b, 2022; Wang et al., 2023b,i; Zhang et al., 2024d). There are also some papers dealing with energy related tasks, specifically fault diagnosis and degradation analysis of photovoltaic systems (Fan et al., 2024; Van Gompel et al., 2023) and of energy networks (Zhang et al., 2024a). They are included in this thematic group because of their specific focus on fault classification rather than on energy-related time series forecasting. It should also be underlined that the majority of these papers aim at solving a classification task, which is typical of anomaly detection and fault diagnosis. As for RUL estimation, the quantity to be predicted is the RUL itself. For this reason, we do not make specific reference to forecasting time horizons, unlike in the other subsections, since the goal here is to estimate the RUL rather than to forecast data over future time intervals.

The majority of the collected papers related to this theme were published in 2024, and the most popular journal for these topics is *IEEE Transactions on Instrumentation and Measurement* by IEEE, with 6 out of 35 papers. It can be observed that the majority of the articles are pub-

Table 26
Comparison of the average accuracy of the different models on the PeMS04 dataset for a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE. The results of the models marked with * are taken from papers in the "Generic" group. The smallest errors are underlined. Numbers from the original papers.

Time horizon	60 min		
Metrics	MAE	MAPE	RMSE
AdaSTNet	19.25	12.77	31.26
AGCRN (Bai et al., 2020)	19.83	12.97	32.26
ARIMA	33.73	24.18	48.80
ASTGCN	22.93	16.56	35.22
ASTGNN	18.60	12.36	30.91
Auto-DSTSGN (Jin et al., 2023a)	18.85	13.21	30.48
Autoformer*	23.76	18.01	36.59
AutoSTG	20.38	14.12	32.51
AutoSTS (Li et al., 2022b)	18.76	12.84	30.31
CL4ST* (Tang et al., 2023a)	18.49	12.00	30.17
Crossformer*	20.40	14.62	32.79
DCGCN (Gu et al., 2023)	20.28	-	31.65
DCRNN	24.70	17.12	38.12
DGCRN*	19.04	12.80	30.82
DMGF-Net (Li et al., 2023e)	20.59	13.63	32.43
DSA-NET	22.79	16.03	35.77
DSTAGNN (Lan et al., 2022)	19.30	12.70	31.46
DSTGN* (Li et al., 2023j)	18.61	12.31	30.79
DSTIGNN* (Gao et al., 2023c)	18.41	12.45	29.97
DyHSL	17.66	12.42	29.46
EnhanceNet	20.44	13.58	32.37
FEDFormer*	22.86	16.04	35.07
FOGS*	19.74	13.05	31.66
FourierGNN	22.98	15.14	36.23
Gboot (Gao et al., 2024a)	19.28	12.58	31.02
GL-STGTN (Li et al., 2024g)	18.20	12.48	29.71
GMAN*	20.93	14.06	33.34
GMSDR*	20.49	14.15	32.13
GODERN-FS* (Zhan et al., 2023)	19.17	12.74	30.96
GRU	23.68	16.44	39.27
GWN	19.36	13.31	31.72
HA	38.03	27.88	59.24
LSGCN	21.53	13.18	33.86
LSTM	23.81	18.12	36.62
MTGNN*	24.89	17.29	39.66
MTGODE*	19.55	13.08	32.99
PAHNN (Zhao et al., 2024)	16.28	11.98	27.62
PDFormer	25.75	17.55	42.09
SCINet*	19.29	11.89	31.28
SDGL* (Li et al., 2023k)	18.65	12.38	31.30
STAGCN (Gu & Deng, 2022)	19.02	12.46	30.75
STCGNN (Yang et al., 2023b)	19.39	12.71	31.17
StemGNN*	21.61	16.10	33.80
STExplainer* (Tang et al., 2023b)	18.57	12.13	30.14
STFGCN	19.83	13.02	31.88
STG2Seq	25.20	18.77	38.48
STGCN	21.16	13.83	34.89
STGDN (Fan et al., 2023)	19.10	12.60	30.83
STGNCDE*	19.21	12.76	31.09
STGODE	20.84	13.76	32.84
ST-GTNN	20.08	13.31	32.18
STIDGCN*	18.47	12.42	29.90
STNorm	19.21	13.05	32.30
STSGCN	21.19	13.90	33.65
STWave (Fang et al., 2023a)	18.50	12.43	30.39
STWawe+ (Fang et al., 2024)	18.25	12.21	30.14
SVR	28.70	19.20	44.56
TAMP-S2GCNets*	19.74	13.22	31.74
TCN	23.22	15.59	37.26
TimesNet	21.63	13.15	34.90
Transformer	21.10	15.13	31.46
TSGDC (Wei et al., 2024b)	18.80	12.67	31.08
VAR	23.75	18.09	36.66
W-DSTAGNN (Jakhmola et al., 2024)	19.30	12.70	31.28
Z-GCNETS (Chen et al., 2021)	19.50	12.78	31.61

Table 27
Comparison of the average accuracy of the different models on the PeMS07 dataset for a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE. The smallest errors are underlined. Numbers from the original papers.

Time horizon	60 min		
Metrics	MAE	MAPE	RMSE
AdaSTNet	21.33	8.94	35.04
AGCRN	22.37	9.12	36.55
AMGCN (Li et al., 2024a)	19.83	8.19	31.03
ARIMA	38.17	19.46	59.27
ASTGCN	24.01	10.73	37.87
Auto-DSTSGN (Jin et al., 2023a)	20.08	8.57	33.02
AutoSTG	23.22	9.95	36.47
AutoSTS (Li et al., 2022b)	20.26	8.54	33.09
CL4ST* (Tang et al., 2023a)	20.20	8.53	34.06
DCGCN (Gu et al., 2023)	22.06	-	34.66
DCRNN	25.22	11.82	38.61
DGCRN	19.91	8.32	31.47
DMSTG	19.98	8.56	33.08
DMSTGCN	20.77	8.94	33.67
DSTAGNN (Lan et al., 2022)	21.42	9.01	34.51
DSTCGCN	20.37	8.64	33.47
DyHSL	18.84	8.11	31.65
Gboot	21.35	9.02	34.43
GMAN	21.56	9.51	34.97
GMSDR*	22.27	9.86	34.94
GWN	26.85	12.12	42.78
FOGS*	21.28	8.95	34.88
FourierGNN	25.47	10.76	39.69
HA	45.12	24.51	65.64
LSGCN	27.31	11.98	41.46
LSTM	29.98	13.20	45.94
MTGNN	20.57	9.12	33.54
PAHNN (Zhao et al., 2024)	17.35	7.64	29.78
PDFormer	23.92	11.62	36.76
PGCN	20.03	8.78	32.54
PYNet (Hu et al., 2023)	19.61	8.36	32.85
RGSL	20.73	8.71	34.48
RST-LTG (Li et al., 2024c)	19.49	8.26	32.91
SLCNN	20.38	8.85	33.27
SPGCL	31.35	18.32	46.34
STAGCN (Gu & Deng, 2022)	21.10	8.92	34.10
StemGNN	22.23	9.20	36.46
STExplainer* (Tang et al., 2023b)	20.00	8.51	33.45
STFGCN	22.07	9.21	35.80
STFGNN	23.46	9.21	36.60
STG2Seq	32.77	20.16	47.16
STGBN (Fan et al., 2023)	21.33	8.94	35.04
STGCN	25.38	11.08	38.78
STGNCDE*	20.53	8.80	33.84
STGODE	22.59	10.14	37.54
ST-GRAT	20.69	9.06	33.01
STNorm	20.59	8.61	34.86
STSGCN	24.26	10.21	39.03
STWave (Fang et al., 2023a)	19.94	8.38	33.88
STWave+ (Fang et al., 2024)	19.59	8.17	33.53
SVR	32.49	14.26	50.22
TAMP-S2GCNets*	21.84	9.24	35.42
TCN	32.72	14.26	42.23
TimesNet	25.12	10.60	40.71
Transformer	22.07	10.12	34.21
TSGDC (Wei et al., 2024b)	19.96	8.54	33.25
VAR	50.22	32.22	75.63
Z-GCNETs	21.77	9.25	35.17

lished in IEEE journals. As for conference venues, 4 out of 7 conference papers were presented at CIKM.

5.6.2. Datasets

Table 29 contains a list of the public datasets used in the selected papers, with the links to access them.

The two popular datasets are C-MAPSS and N-CMAPSS, two well-known datasets for RUL prediction provided by NASA. C-MAPSS describes the deterioration of aircraft engines by recording temper-

Table 28
Comparison of the average accuracy of the different models on the PeMS08 dataset for a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE. The results of the models marked with * are taken from papers in the "Generic" group. The smallest errors are underlined. Numbers from the original papers.

Time horizon	60 min		
Metrics	MAE	MAPE	RMSE
AdaSTNet	15.72	9.98	24.72
AGCRN (Bai et al., 2020)	15.95	10.09	25.22
ARIMA	31.09	22.73	44.32
ASTGCN	18.25	11.64	28.06
ASTGNN	15.00	9.50	24.70
Auto-DSTSGN (Jin et al., 2023a)	14.74	9.45	23.76
Autoformer*	21.04	15.98	31.33
AutoSTG	16.37	10.36	25.46
AutoSTS (Li et al., 2022b)	14.65	9.49	23.52
CL4ST* (Tang et al., 2023a)	14.74	9.61	24.17
Crossformer*	16.25	11.14	26.14
DCGCN (Gu et al., 2023)	15.68	-	24.39
DCRNN	16.82	10.92	26.36
DHSL* (Wang et al., 2024g)	15.19	9.86	24.61
DGCRN	16.22	12.06	26.10
DMGF-Net (Li et al., 2023e)	16.48	10.56	25.73
DMSTG	13.85	9.26	23.30
DSA-NET	17.14	11.32	26.96
DSTAGNN (Lan et al., 2022)	15.67	-	25.37
DSTCGCN	15.18	9.68	24.49
DSTIGNN* (Gao et al., 2023c)	13.88	9.04	23.64
DyHSL	14.01	8.87	22.91
EnhanceNet	16.33	10.39	25.56
FC-GAGA	19.41	13.53	30.22
FEDformer*	19.55	13.58	29.30
FNN	24.24	16.21	37.57
FOGS*	15.73	9.88	24.92
Gboot (Gao et al., 2024a)	15.54	9.76	24.53
GL-STGTN (Li et al., 2024g)	14.00	9.50	23.41
GMAN	15.31	10.13	24.92
GMSDR (Liu et al., 2022a)	16.36	10.28	25.58
GODERN-FS* (Zhan et al., 2023)	15.59	9.95	24.79
GRU	22.00	13.33	36.24
GWN	15.07	9.51	23.85
HA	34.86	24.07	52.04
iDCGCN	15.56	-	25.02
LSGCN	17.73	11.20	26.76
LSTM	22.20	14.20	34.06
MRA-BGCN	18.87	12.96	28.56
MTGNN	15.71	10.03	24.62
MTGODE*	15.61	10.15	25.96
PAHNN (Zhao et al., 2024)	13.58	8.35	22.11
PYNet (Hu et al., 2023)	14.03	9.39	23.84
RGSL	15.49	9.96	24.80
RST-LTG (Li et al., 2024c)	13.61	9.05	23.15
SCINet*	15.78	9.97	24.60
SDGL* (Li et al., 2023k)	14.93	9.61	24.13
SNAS4MTF (Chen et al., 2025)	15.07	9.67	24.00
STAGCN (Gu & Deng, 2022)	15.36	9.80	24.32
STCGNN (Yang et al., 2023b)	15.55	10.02	24.61
StemGNN	15.91	10.90	25.44
STExplainer* (Tang et al., 2023b)	14.59	9.80	23.91
STFGNN	16.64	10.60	26.25
STGNCDE*	15.45	9.92	24.81
STG2Seq	20.17	17.32	30.71
STGBN (Fan et al., 2023)	15.35	9.71	24.18
STGCN	17.50	11.29	27.09
STGMN	16.04	-	24.18
STGODE	16.79	10.58	26.01
ST-GTNN	16.51	10.45	25.19
STIDGCN*	14.10	9.15	23.72
STMetaNet	18.75	14.49	27.50
STNorm	15.39	9.91	24.80
STSGCN	17.13	10.96	26.80
STWave (Fang et al., 2023a)	13.42	8.90	23.40
STWave+ (Fang et al., 2024)	13.21	8.63	23.04
SVR	23.25	14.64	36.16
TAMP-S2GCNets*	13.36	10.15	25.98

Table 28
Continued

TCN	22.72	14.03	35.79
TimesNet	19.01	11.83	30.65
VAR	19.19	13.10	29.81
Z-GCNETs* (Chen et al., 2021)	15.76	10.01	25.11

ature, pressure, and fan speed during the cruise phase (https://ntrs.nasa.gov/api/citations/20070034949/downloads/20070034949.pdf). N-CMAPSS is an extended version of C-MAPSS, whose records cover climbing, cruising, and descending flight conditions (https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/). Almost no papers use exogenous variables, with the exception of Van Gompel et al. (2023), which evaluates the impact of meteorological variables on fault diagnosis of photovoltaic systems. Other popular datasets are SWaT and WaDi. The secure water treatment dataset (SWaT) is a cybersecurity dataset that includes data collected from 51 sensors and actuators over a continuous period of 11 days. During this time, the system operated under normal conditions for 7 days and was subjected to attack scenarios for 4 days. The dataset contains both network traffic and physical process data recorded from all devices. The water distribution (WaDi) dataset is an extension of SWaT involving a larger setup of 127 sensors and actuators monitored for 16 consecutive days.

The time granularity of the studied time series is highly variable, ranging from 1 h to fractions of seconds. Many papers report the frequency of the studied sensors, with values ranging from 1 Hz to 50 kHz. Most datasets are normalized, by either using min-max normalization or Z-score normalization. In some papers, a data augmentation procedure is employed to mitigate the natural imbalance between the number of normal and anomalous conditions.

5.6.3. Types of models

Almost half of the proposed spatio-temporal GNN models (19 out of 40 papers) fall under the category of pure convolutional GNNs, followed by 15 attentional GNNs, 2 hybrid models, and one recurrent model (Feng et al., 2024a). One paper (Ning et al., 2023) uses both convolutional and attentional GNNs, one paper (Gao et al., 2024b) uses a variant of the convolutional GNN, and the description of another one (Mylonas & Chatzi, 2021) does not clarify which class of the taxonomy it belongs to. Almost all the models have a graph learning module, so that the graph structure is rarely defined a priori by the researchers. Three papers (Li et al., 2021a; Ning et al., 2023; Wang et al., 2023b) use the visibility graph algorithm proposed by Lacasa et al. (2008) for converting the time series into a graph.

The most common loss functions used within this thematic group are the cross entropy function for classification problems, and MSE or RMSE for RUL forecasting problems. Most of the papers mention the Python language and the PyTorch library, but only the papers listed in Table 30 provide the links to the related source codes.

5.6.4. Benchmark models

Table 31 presents the benchmark models employed in the "Predictive monitoring" thematic group by at least two articles examined.

In this thematic group there is a high variety of benchmarks used, and before 2024 only few papers share a benchmark model in the GNN category. The most popular benchmarks are two classic machine learning models, the CNN and the LSTM network. Not surprisingly, almost no statistical or mathematical benchmark models were used, since they are more frequently used in forecasting problems than in classification problems.

Among the GNN benchmarks, some of them have been specifically developed for remaining useful life prediction or predictive monitoring tasks, such as the hierarchical attention graph convolutional network (HAGCN) (Li et al., 2021e), the spatio-temporal fusion attention (STFA) (Kong et al., 2022), and the graph deviation network (GCN) (Deng & Hooi, 2021). In the HAGCN model the spatial dependencies are modeled by a hierarchical graph representation layer, and a bidirectional long-short term memory network is used for modeling temporal dependencies of sensor measurements. As for the STFA model, it integrates some *a priori* knowledge about the equipment's structure with a spatio-temporal deep learning architecture which employs LSTM cells and an attention mechanism. Finally, the GDN model learns a graph structure that represents the relationships between sensors, and aims to detect deviations from these patterns by using an attentional GNN. The source code for the GDN model is available at https://github.com/d-ailin/GDN.

5.6.5. Results

The reported results show that the proposed GNN models clearly outperform the benchmarks. The accuracy of the models is evaluated using different metrics, depending on whether the context is classification or forecasting. For classification tasks, several studies present confusion matrices and calculate accuracy percentages. For RUL forecasting problems instead, the most commonly used metrics are the RMSE and the score function.

The only results that can be compared across many papers are those for the C-MAPSS dataset. Table 32 shows the accuracy of the different models, expressed in terms of RMSE and score function.

In general, the best results on the different sub-datasets are achieved by the convolution-graph attention network (ConvGAT) (Chen & Zeng, 2023) and the dual-stream spatio-temporal fusion network (DS-STFN) (Zhang et al., 2024d) models. The ConvGAT model applies independent convolutional kernels to each feature of the input time series, and passes the resulting values to a graph attention network, with graph structure defined using cosine similarity. Finally, a fully connected layer outputs the RUL prediction. The DS-STFN model organizes the data into grid-structured and graph-structured formats, with the graph structure defined by cosine similarity. A temporal convolutional network with self-attention extracts temporal features from the grid data, and, in parallel, a convolutional graph transformer module captures spatial features from the graph data. The spatial and temporal features are then fused to predict the RUL.

Other pairs of papers with comparable results are the ones by Han and Woo (2022) and Lee et al. (2023) for SWaT and WaDi datasets and the ones by Guo et al. (2024) and Liu et al. (2024e) for the MSL dataset. However, due to space limitations, tables comparing just two studies are not included here.

5.7. Generic

This subsection includes all the papers that do not specifically address a problem in the specific themes discussed so far. These papers present results on benchmark case studies, for which the related datasets span different thematic groups at once. In particular, the focus is on papers that do not discuss or mention any specific case study prior to the experimental section, or analyze datasets from multiple fields. The reason for this choice is that they are considered to explore broader methodologies or frameworks that are applied to diverse datasets without a declared focus on a particular case.

For instance, some subsets of papers within the "Generic" group focus on forecasting in presence of missing data (e.g., Marisca et al., 2024; Yu et al., 2024a), or of irregularly sampled time series (e.g., Oskarsson et al., 2023; Yalavarthi et al., 2024; Zhang et al., 2024e,f, 2022b). Notably, the majority of these studies have been published in conferences rather than in journals.

Moreover, some papers in this section also tackle some theoretical issues. For example, Liu et al. (2022d) prove a theorem that provides a theoretical bound on the approximation error of the module that learns the dynamic variable dependence. Another example can be found in Zhang et al. (2023k), where the authors theoretically establish that the generalization error bound of their model is related to various components of the GAT model, such as the number of attention heads, the

Table 29
List of public datasets in the "Predictive monitoring" group and their corresponding links.

Dataset	Used in	Link
Air quality China	(Li et al., 2022d)	https://www.aqistudy.cn/historydata/
Air quality - TPS	(Li et al., 2022d)	https://www.kaggle.com/amritpal333/tps-july-2021-original-dataset-clean
C-MAPSS	(Wang et al., 2023i), (Chen & Zeng, 2023), (Wang et al., 2023b), (Kong et al., 2022), (Zhang et al., 2024d) and (Kong et al., 2024b)	https://ntrs.nasa.gov/api/citations/20070034949/downloads/20070034949.pdf
CWRU bearing dataset	(Li et al., 2021a), (Lei et al., 2023) and (Wang et al., 2024c)	http://csegroups.case.edu/bearingdatacenter/home
HAI security dataset	(Han & Woo, 2022)	https://github.com/icsdataset/hai
Herbert river water level	(Buchhorn et al., 2023)	https://zenodo.org/records/8053359
Intelligent maintenance system (IMS)	(Gao et al., 2024b)	https://www.nasa.gov/intelligent-systems-division
JNU bearing dataset	(Li et al., 2021a)	http://mad-net.org:8765/explore.html?id=9&t=0.9355271549540183[†]
MFPT	(Lei et al., 2023)	https://api.semanticscholar.org/CorpusID:26870683 (source paper)
Mars science laboratory rover (MSL)	(Guo et al., 2024), (He et al., 2024b), (Liu et al., 2024e) and (Lee et al., 2023)	https://doi.org/10.1145/3219819.3219845 (source paper)
NASA battery dataset	(Wei & Wu, 2023)	http://ti.arc.nasa.gov/project/prognostic-data-repository
NASA prognostics data	(Zhang et al., 2023f)	https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/#bearing
N-CMAPSS	(Wang et al., 2023i) and (Wang et al., 2023b)	https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/
NREL PV	(Van Gompel et al., 2023)	https://www.nrel.gov/
PRONOSTIA	(Mylonas & Chatzi, 2021) and (Yang et al., 2022)	https://hal.science/hal-00719503/document (source paper)
Pooled server metrics (PSM)	(Liao et al., 2024b) and (Guo et al., 2024)	https://doi.org/10.1145/3447548.3467174 (source paper)
PV degradation	(Fan et al., 2024)	https://github.com/Yangxin666/ST-GTrend/tree/main/Datasets
SEU bearing dataset	(Li et al., 2021a)	https://github.com/cathysiyu/Mechanical-datasets
Soil moisture active passive satellite (SMAP)	(Liao et al., 2024b), (Guo et al., 2024), (Zheng et al., 2024a), (He et al., 2024b) and (Lee et al., 2023)	https://doi.org/10.1145/3219819.3219845 (source paper)
Server machine dataset (SMD)	(Liao et al., 2024b), (Zheng et al., 2024a) and (Liu et al., 2024e)	https://github.com/NetManAIOps/OmniAnomaly
Secure water treatment (SWaT)	(Zheng et al., 2024b), (Liao et al., 2024b), (Guo et al., 2024), (Zheng et al., 2024a), (He et al., 2024b), (Han & Woo, 2022), (Liu et al., 2024e), (Malarkkan et al., 2024), (Li et al., 2024e) and (Lee et al., 2023)	https://itrust.sutd.edu.sg/itrust-labs_datasets/dataset_info/
Water distribution (WaDi)	(Zheng et al., 2024b), (Liao et al., 2024b), (Zheng et al., 2024a), (He et al., 2024b), (Han & Woo, 2022), (Liu et al., 2024e), (Malarkkan et al., 2024), (Li et al., 2024e) and (Lee et al., 2023)	https://itrust.sutd.edu.sg/itrust-labs_datasets/dataset_info/
Wireless capsule endoscopy images	(Gao et al., 2024b)	https://doi.org/10.1055/s-0043-105488 (source paper)
XJTUGearbox and XJTUSpurgear	(Lei et al., 2023) and (Wang et al., 2024f)	http://dx.doi.org/10.1016/j.ymssp.2021.108653 (source paper)

Table 30
List of source codes of the "Predictive monitoring" models in the review.

Model	Link
Causality enhanced global-local graph neural network (CEGLo-GNN) (Sun et al., 2024b)	https://github.com/YueYueXia/CEGLo-GNN
Dual time-oriented graph attention networks (DuoGAT) (Lee et al., 2023)	https://github.com/ByeongtaePark/DuoGAT
Graph deviation network + (GDN+) (Buchhorn et al., 2023)	https://github.com/KatieBuc/gnnad/releases
Graph network with causal connectivity and temporal convolutional neural network feature extractor (Mylonas & Chatzi, 2021)	https://github.com/mylonasc/gnn-tcnn
Spectral multi-view causal graph fusion based anomaly detection (SMV-CGAD) (Malarkkan et al., 2024)	https://github.com/arunvignesh28/SMV-CGAD[†]
Spatio-temporal graph neural network empowered long-term trend analysis system (ST-GTrend) (Fan et al., 2024)	https://github.com/Yangxin666/ST-GTrend
Graph attention networks with topological analysis (TopoGDN) (Liu et al., 2024e)	https://github.com/ljj-cyber/TopoGDN

number of neighboring nodes, the Frobenius norm of the weight matrices, and the norm of the input features.

5.7.1. Overview

A significant number of papers (77 out of 366) have been categorized under the "Generic" thematic group. The majority of these works commit themselves to address a multivariate time series forecasting problem not necessarily limited to a specific field. This "Generic" set includes 4 papers from 2002, 7 from 2021, 11 from 2022, 28 from 2023, and 27 from 2024, highlighting the recent interest in applying GNNs in cross-disciplinary contexts. These papers are scattered across various journals, with the exception of *Expert Systems with Applications* by Elsevier, *IEEE Transactions on Knowledge and Data Engineering* by IEEE, and *Information Sciences* by Elsevier, which published 4 and 3 of the selected papers, respectively. The three conference venues with the highest number of papers are NeurIPS with 6 papers, CIKM with 5 papers, and KDD with 4 papers.

5.7.2. Datasets

The selected papers make use of the datasets listed in Table 33 in their experiments.

It should be noted that multiple recurring datasets can be considered as benchmarks for this community. Some of these were discussed in the previous subsections (e.g., METR-LA, PeMS datasets). Hence, if the results for these datasets were already shown in previous subsections, they will not be discussed again here. Instead, they will be just marked with the symbol ⋆ in the tables of the previous subsections.

Table 31
List of benchmark models in the "Predictive monitoring" group divided per category.

Category	Model	Used in
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	(Buchhorn et al., 2023) and (Zhang et al., 2024a)
Non-GNN machine learning methods	Auto-encoder (AE)	(Zheng et al., 2024a), (Han & Woo, 2022), (Lee et al., 2023) and (Hojjati et al., 2023)
	Feature-attention based bidirectional GRU and CNN model (AGCNN) (Zhu et al., 2022)	(Chen & Zeng, 2023), (Wang et al., 2023b), (Kong et al., 2022), (Zhang et al., 2024d) and (Kong et al., 2024b)
	Attention-based long-short term memory network	(Chen & Zeng, 2023), (Kong et al., 2022) and (Kong et al., 2024b)
	Anomalous rhythm detection using adversarially generated time series (BeatGAN) (Zhou et al., 2019)	(Guo et al., 2024) and (Zheng et al., 2024a)
	Bidirectional long-short term memory network (BiLSTM) (Graves & Schmidhuber, 2005)	(Wang et al., 2023i), (Chen & Zeng, 2023), (Wang et al., 2023b), (Kong et al., 2022), (Feng et al., 2024a) and (Kong et al., 2024b)
	Convolutional neural network (CNN)	(Li et al., 2022d), (Wang et al., 2023i), (Chen & Zeng, 2023), (Wang et al., 2023b), (Yang et al., 2022), (Kong et al., 2022), (Chen et al., 2024a), (Kovalenko et al., 2024), (Wang et al., 2024b), (Zhang et al., 2024a) and (Kong et al., 2024b)
	Convolutional neural network with long-short term memory network (CNN-LSTM)	(Wang et al., 2023b) and (Feng et al., 2024a)
	Crossformer (Zhang & Yan, 2023)	(Wang et al., 2023i) and (Sun et al., 2024b)
	Deep autoencoding gaussian model (DAGMM) (Zong et al., 2018)	(Guo et al., 2024), (Zheng et al., 2024a), (Han & Woo, 2022), (Li et al., 2024e) and (Lee et al., 2023)
	Deep belief network (DBN) (Zhang et al., 2017a)	(Kong et al., 2022) and (Kong et al., 2024b)
	Decision tree (DT)	(Li et al., 2022d) and (Zhang et al., 2024a)
	Feed-forward neural network (FNN)	(Li et al., 2021a), (Mylonas & Chatzi, 2021), (Kovalenko et al., 2024) and (Zhang et al., 2024d)
	Genetic algorithm approach on restricted Boltzmann-based long-short term memory network (GA + RBM + LSTM) (Listou Ellefsen et al., 2019)	(Kong et al., 2022) and (Kong et al., 2024b)
	Gradient boosting (GB)	(Wang et al., 2023b) and (Zhang et al., 2024a)
	Gated recurrent unit (GRU)	(Van Gompel et al., 2023), (Yang et al., 2022), (Kovalenko et al., 2024) and (Zhang et al., 2024a)
	Integrated multi-head dual sparse self-attention network (IMDSSN) (Zhang et al., 2023b)	(Wang et al., 2023b), (Zhang et al., 2024d) and (Kong et al., 2024b)
	Isolation forest	(Li et al., 2023g), (Guo et al., 2024) and (Malarkkan et al., 2024)
	k-nearest neighbors (KNN)	(Gao et al., 2024b), (Zhang et al., 2024a), (Han & Woo, 2022) and (Lee et al., 2023)
	Local outlier factor (LOF) (Breunig et al., 2000)	(Gao et al., 2024b) and (Guo et al., 2024)
	Long-short term memory network (LSTM)	(Li et al., 2021a), (Wang et al., 2023b), (Kong et al., 2022), (Wei & Wu, 2023), (Chen et al., 2024a), (Feng et al., 2024a), (Zhang et al., 2024a) and (Kong et al., 2024b)
	Long-short term memory-based variational auto-encoder (LSTM-VAE)	(Li et al., 2023g), (Zheng et al., 2024b), (Liao et al., 2024b), (Zheng et al., 2024a), (He et al., 2024b), (Han & Woo, 2022), (Liu et al., 2024e) and (Hojjati et al., 2023)
	Multivariate anomaly detection with GAN (MAD-GAN) (Li et al., 2019)	(Li et al., 2023g), (Han & Woo, 2022), (Liu et al., 2024e) and (Lee et al., 2023)
	OmniAnomaly (Su et al., 2019)	(Zheng et al., 2024b), (Liao et al., 2024b), (Guo et al., 2024), (Zheng et al., 2024a), (He et al., 2024b) and (Liu et al., 2024e)
	Random forest (RF)	(Wang et al., 2023b), (Zhang et al., 2024d) and (Zhang et al., 2024a)
	Support vector machine (SVM)	(Li et al., 2022d), (Han & Woo, 2022), (Zhang et al., 2024d), (Wang et al., 2024b), (Zhang et al., 2024a), (Malarkkan et al., 2024), (Lee et al., 2023) and (Hojjati et al., 2023)
	Deep transformer networks for anomaly detection (TranAD) (Tuli et al., 2022)	(Zheng et al., 2024a), (He et al., 2024b), (Liu et al., 2024e) and (Li et al., 2024e)
	Transformer (Vaswani et al., 2017)	(Wang et al., 2023i), (Wang et al., 2023b), (Feng et al., 2024a), (Zhang et al., 2024d), (Liao et al., 2024b), (Kong et al., 2024b) and (He et al., 2024b)
	Unsupervised anomaly detection on multivariate time series (USAD) (Audibert et al., 2020)	(Liao et al., 2024b), (Zheng et al., 2024a), (He et al., 2024b), (Han & Woo, 2022), (Lee et al., 2023) and (Hojjati et al., 2023)
GNN methods	Adaptive graph convolutional recurrent network (AGCRN) (Bai et al., 2020)	(Zhang et al., 2023f) and (Sun et al., 2024b)
	Diffusion convolutional recurrent neural network (DCRNN) (Li et al., 2018)	(Li et al., 2024b) and (Sun et al., 2024b)
	Fused sparse autoencoder and graph network (FuSAGNet) (Han & Woo, 2022)	(Li et al., 2023g), (Liao et al., 2024b) and (Li et al., 2024e)
	Graph attention network (GAT) (Veličković et al., 2018)	(Yuan et al., 2023), (Lei et al., 2023), (Feng et al., 2024a) and (Zhang et al., 2024a)
	Graph convolutional network (GCN)	(Yuan et al., 2023), (Li et al., 2021a), (Yang et al., 2022), (Lei et al., 2023), (Chen et al., 2024a), (Wang et al., 2024f) and (Wang et al., 2024b)
	Graph deviation network (GDN) (Deng & Hooi, 2021)	(Li et al., 2023g), (Zheng et al., 2024b), (Liao et al., 2024b), (Guo et al., 2024), (Zheng et al., 2024a), (Han & Woo, 2022), (Liu et al., 2024e), (Li et al., 2024e), (Lee et al., 2023) and (Hojjati et al., 2023)
	Gated graph convolutional network (GGCN) (Wang et al., 2022a)	(Chen & Zeng, 2023) and (Zhang et al., 2024d)

Table 31
Continued

	Graph WaveNet (GWN) (Wu et al., 2019)	(Zhang et al., 2023f), (Li et al., 2024b) and (Sun et al., 2024b)
	Hierarchical attention graph convolutional network (HAGCN) (Li et al., 2021e)	(Wang et al., 2023i), (Chen & Zeng, 2023) and (Zhang et al., 2024d)
	Multivariate time-series anomaly detection via graph attention network (MTAD-GAT) (Zhao et al., 2020a)	(Liao et al., 2024b), (Han & Woo, 2022), (Li et al., 2024e) and (Lee et al., 2023)
	Multivariate time series forecasting with graph neural network (MTGNN) (Wu et al., 2020c)	(Feng et al., 2024a) and (Buchhorn et al., 2023)
	Spatio-temporal fusion attention (STFA) (Kong et al., 2022)	(Chen & Zeng, 2023), (Wang et al., 2023b), (Zhang et al., 2024d) and (Kong et al., 2024b)
	Spatio-temporal graph convolutional network (STGCN) (Yu et al., 2018)	(Zhang et al., 2023f), (Wang et al., 2023i), (Feng et al., 2024a), (Zhang et al., 2024d) and (Li et al., 2024b)

Table 32
Comparison of the accuracy of the different models on the C-MAPSS dataset on sub-datasets FD001–FD004, expressed in terms of RMSE and score function. The smallest errors are underlined. Numbers from the original papers.

Sub-dataset	FD001		FD002		FD003		FD004	
Metrics	RMSE	Score	RMSE	Score	RMSE	Score	RMSE	Score
1D CNN	12.61	273.70	22.36	10412.00	12.64	284.10	23.31	12466.00
2D CNN	18.45	1286.70	30.29	13570.00	19.82	1596.20	29.16	7886.40
AGCNN	12.42	225.51	19.43	1492.76	13.39	227.09	21.50	3392.60
ATT-LSTM	13.95	320.00	17.65	2102.00	12.72	223.00	20.21	3100.00
BiGRU-AS	13.68	284.00	20.81	2454.00	15.53	428.00	27.31	4708.00
Bi-LSTM	13.65	295.00	23.18	4130.00	13.74	317.00	24.86	5430.00
BiLSTM-ED	14.74	273.00	22.07	3099.00	17.48	574.00	23.49	3202.00
BLCNN	13.18	302.28	19.09	1557.56	13.75	381.37	20.97	3858.78
CDSG (Wang et al., 2023b)	11.26	188.00	18.13	1740.00	12.03	218.00	19.73	2332.00
ChebyNet-EdgePool	15.21	450.22	16.28	1229.22	14.67	421.02	16.26	1159.74
CNN-LSTM	14.40	290.00	27.23	9869.00	14.32	316.00	26.69	6594.00
CNN-Transformer	12.25	198.00	17.08	1575.00	13.39	290.00	19.86	1741.00
ConvGAT (Chen & Zeng, 2023)	11.34	197.43	14.12	771.61	10.97	235.26	15.51	1231.17
C-Transformer	13.79	475.46	16.11	2214.59	17.10	939.10	19.77	3237.37
DBN	15.21	417.59	27.12	9031.64	14.71	442.43	29.88	7954.51
DCNN	12.61	273.70	22.36	10412.00	12.64	284.10	23.31	12466.00
DSAN	13.40	242.00	22.06	2869.00	15.12	497.00	21.03	2677.00
DS-STFN (Zhang et al., 2024d)	10.92	161.35	13.77	946.34	10.01	150.42	15.53	1079.91
Earlier CNN	18.45	1287.00	30.29	13570.00	19.82	1596.00	29.16	7886.00
ELM	17.27	523.00	37.28	498149.97	18.90	573.78	38.43	121414.00
GA + RBM + LSTM	12.56	231.00	22.73	3366.00	12.10	251.00	22.66	2840.00
GA-Transformer	11.63	215.00	15.99	1133.00	11.35	228.00	20.15	2672.00
GAT-DAT	13.83	318.60	14.81	1163.80	14.85	438.50	16.80	1928.60
GAT-EdgePool	13.53	309.59	15.07	1380.41	14.66	470.74	17.60	1726.53
GAT-TopkPool	13.21	303.18	17.25	5338.80	15.36	507.52	21.44	2971.93
GB	15.67	474.01	29.09	87280.06	16.84	576.72	29.01	17817.92
GGCN	11.82	186.70	17.24	1493.70	12.21	245.19	17.36	1371.50
HAGCN	11.93	222.30	15.05	1144.10	11.53	240.30	15.74	1218.60
HDNN	13.02	245.00	15.24	1282.42	12.22	287.72	18.16	1527.42
HGNN-ACGF	12.58	218.04	21.67	4584.97	12.40	248.47	22.43	2737.86
IMDSSN	12.14	206.11	17.40	1775.15	12.35	229.54	19.78	2852.81
LSTM	16.14	338.00	24.49	4450.00	16.18	852.00	28.17	5550.00
LSTMBS	14.89	481.00	26.86	7982.00	15.11	493.00	27.11	5200.00
MODBN	15.04	334.23	25.05	5585.00	12.51	421.91	28.66	6557.00
MS-CNN	11.44	196.22	19.35	3747.00	11.67	241.89	22.22	4844.00
RF	17.91	479.75	29.59	70456.86	20.27	711.13	31.12	46567.63
SBI	13.58	228.00	19.59	2650.00	19.16	1727.00	22.15	2901.00
SMDN	13.40	272.00	-	-	-	-	23.40	4302.00
STFA (Kong et al., 2022)	11.35	194.44	19.17	2493.09	11.64	224.53	21.41	2760.13
STP-GNN (Kong et al., 2024b)	11.38	192.17	15.81	1094.81	11.02	199.58	17.77	1692.19
TATFA-Transformer	12.21	261.50	15.07	1359.70	11.23	210.21	18.81	2506.35
Transformer	12.92	276.27	22.64	1960.25	13.04	284.41	24.81	3892.24

The four most common datasets are Electricity consumption, Exchange-rate, Solar-Energy and Traffic, all available at https://github.com/laiguokun/multivariate-time-series-data. The Electricity consumption dataset contains the hourly electricity consumption in kWh for 321 customers, recorded from 2012 to 2014. The Traffic dataset describes the road occupancy rates measured by different sensors on the San Francisco Bay area road network from 2015 to 2016, with an hourly granularity. In Solar energy it is recorded the solar power production from 137 photovoltaic plants in Alabama State in 2006, with a 10 minutes granularity. Finally, Exchange rate contains daily exchange rates of 8 countries including Australia, British, Canada, Switzerland, China, Japan, New Zealand and Singapore, from 1990 to 2016.

The University of East Anglia (UEA) dataset includes 30 multivariate time series from many real-world applications, including heart records, electroencephalogram signals, motion data, audio spectra, written characters. Since a large portion of the dataset contains data not related to the focus of this review, the details of the results and models used will not be discussed here. Interested readers are referred to Du et al. (2024),

Table 33
List of public datasets in the "Generic" papers and their corresponding links.

Dataset	Used in	Link
Beijing Traffic	(Chen et al., 2022c)	https://github.com/BuaaPercy/Traffic-DataSet-of-Beijing-Road
Bytom	(Chen et al., 2021), (Chen et al., 2022e) and (Chen et al., 2022d)	https://etherscan.io/
CCMP wind data	(Li et al., 2023j)	http://data.remss.com
CDC US States	(Sun et al., 2024a)	https://gis.cdc.gov/grasp/fluview/fluportaldashboard.html
CER-E	(Cini et al., 2023a)	https://www.ucd.ie/issda/data/commissionforenergyregulationcer/†
Chickenpox	(Bloemheuvel et al., 2023a) and (Rozemberczki et al., 2021)	https://www.kaggle.com/datasets/die9origephit/chickenpox-cases-hungary
China AQI	(Yu et al., 2024a)	https://quotsoft.net/air/
CI earthquakes	(Bloemheuvel et al., 2023a)	https://doi.org/10.5194/adgeo-43-31-2016 (source paper)
C-MAPSS	(Wang et al., 2024k)	https://ntrs.nasa.gov/api/citations/20070034949/downloads/20070034949.pdf
CORAv2.0	(He et al., 2024c)	https://mds.nmdis.org.cn/pages/home.html
COVID-19 CA	(Chen et al., 2022e), (Chen et al., 2022d), (Yi et al., 2023) and (Chen et al., 2023e)	https://www.dropbox.com/sh/n0ajd5l0tdeyb80/AABGn-ejfV1YtRwjf_L0AOsNa?dl=0
COVID-19 England	(Rozemberczki et al., 2021)	https://pytorch-geometric-temporal.readthedocs.io/en/latest/notes/introduction.html#benchmark-datasets
COVID-19 TX	(Chen et al., 2022e) and (Chen et al., 2022d)	https://www.dropbox.com/sh/n0ajd5l0tdeyb80/AABGn-ejfV1YtRwjf_L0AOsNa?dl=0
CSSE COVID-19	(Xu et al., 2024) and (Yi et al., 2023)	https://github.com/CSSEGISandData/COVID-19
CW earthquakes	(Chung et al., 2023)	https://doi.org/10.5194/adgeo-43-31-2016 (source paper)
Decentraland	(Chen et al., 2021) and (Chen et al., 2022e)	https://etherscan.io/
ECG5000	(Huang et al., 2024a), (Xu et al., 2024), (Cao et al., 2020) and (Yi et al., 2023)	https://www.cs.ucr.edu/~eamonn/time_series_data/
Electricity consumption	(Li et al., 2023j), (Gao et al., 2023c), (Jin et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2023c), (Miao et al., 2023), (Sriramulu et al., 2023), (Zhan et al., 2023), (He et al., 2022b), (Li et al., 2024f), (Fang et al., 2023b), (Ye et al., 2022), (Ma et al., 2024), (Wu et al., 2020c), (Cui et al., 2021), (Cao et al., 2020), (Liu et al., 2022d), (Huang et al., 2023b), (Yi et al., 2023) and (Liu et al., 2022c)	https://github.com/laiguokun/multivariate-time-series-data
Electricity consuming load (ECL)	(Wang et al., 2023g), (Kim et al., 2023c) and (Su et al., 2021)	https://archive.ics.uci.edu/ml/datasets/ElectricityLoadDiagrams20112014
Electricity transformer temperature (ETT)	(Zhang et al., 2023j), (Wang et al., 2023g), (Kim et al., 2023c), (Li & Tang, 2024), (Yang et al., 2024b), (Huang et al., 2023b) and (Su et al., 2021)	https://github.com/zhouhaoyi/ETDataset
Energy	(Duan et al., 2023) and (Han et al., 2024a)	http://dx.doi.org/10.1016/j.enbuild.2017.01.083 (source paper)
ENG-RAD	(Marisca et al., 2024)	https://open-meteo.com/
Enron	(Huang et al., 2021b)	https://doi.org/10.1073/pnas.1800683115 (source paper)
Eu-Core	(Huang et al., 2021b)	https://doi.org/10.1145/3018661.3018731 (source paper)
European wind generation	(Ye et al., 2022)	https://www.kaggle.com/datasets/sohier/30-years-of-european-wind-generation
Exchange-rate	(Li et al., 2023j), (Gao et al., 2023c), (Zhang et al., 2023j), (Duan et al., 2023), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2023c), (Miao et al., 2023), (Kim et al., 2023c), (Wang et al., 2022c), (Chung et al., 2023), (He et al., 2022b), (Li & Tang, 2024), (Li et al., 2024f), (Ye et al., 2022), (Wu et al., 2020c), (Cui et al., 2021), (Liu et al., 2022d), (Huang et al., 2023b) and (Liu et al., 2022c)	https://github.com/laiguokun/multivariate-time-series-data
Facebook	(Huang et al., 2021b)	http://networkrepository.com/socfb
GEFCOM 2012	(Chung et al., 2023)	https://doi.org/10.1016/j.ijforecast.2013.07.001 (source paper)
Golem	(Chen et al., 2022e)	https://www.dropbox.com/sh/n0ajd5l0tdeyb80/AABGn-ejfV1YtRwjf_L0AOsNa?dl=0
GraphMSO	(Marisca et al., 2024)	https://github.com/marshka/hdtts/tree/main/config/dataset
Hypertext	(Huang et al., 2021b)	http://networkrepository.com/ia-infect-hyper (source paper)
HZMetro	(Ma et al., 2024)	https://github.com/HCPLab-SYSU/PVCGN/tree/master/data
IDWR Japan prefectures	(Sun et al., 2024a)	https://www.niid.go.jp/niid/en/idwr-e.html
ILI	(Zhang et al., 2023j), (Kim et al., 2023c) and (Chung et al., 2023)	https://gis.cdc.gov/grasp/fluview/fluportaldashboard.html
ISRUC-SLEEP	(Wang et al., 2024k)	https://sleeptight.isr.uc.pt/ISRUC_Sleep/
Jena weather	(Zhang et al., 2023j) and (Huang et al., 2023b)	https://www.bgc-jena.mpg.de/wetter/
KnowAir	(Wang et al., 2024g)	https://github.com/shuowang-ai/PM2.5-GNN
LA Traffic	(Shaik et al., 2024)	https://ladot.lacity.gov/residents/traffic-counts
Loan	(Huang et al., 2021b)	https://ai.ppdai.com/mirror/showCompetitionRisk
Los-loop	(Liang et al., 2024a)	https://github.com/lehaifeng/T-GCN/tree/master/data
Large-scale traffic and weather events (LSTW)	(Shaik et al., 2024)	https://smoosavi.org/datasets/lstw
METR-LA	(Cini et al., 2023b), (Jin et al., 2023c), (Guo et al., 2023a), (Chen et al., 2023c), (Chen & Xie, 2022), (Bloemheuvel et al., 2023a), (Wang et al., 2024i), (Huang et al., 2024a), (Sun et al., 2024a), (Yang et al., 2024b), (Shang et al., 2021), (Yu et al., 2024a), (Fang et al., 2023b), (Lu & Li, 2020), (Wu et al., 2020c), (Cao et al., 2020), (Yi et al., 2023), (Cini et al., 2023a) and (Oskarsson et al., 2023)	https://www.kaggle.com/datasets/annnnguyen/metr-la-dataset
Metro	(Wang et al., 2024g)	https://lbs.amap.com/
MIMIC	(Han et al., 2023), (Yalavarthi et al., 2024) and (Zhang et al., 2024e)	https://doi.org/10.1038/sdata.2016.35 (source paper)
Montevideo buses	(Rozemberczki et al., 2021)	https://pytorch-geometric-temporal.readthedocs.io/en/latest/notes/introduction.html#benchmark-datasets
MOOC network	(Li et al., 2023h)	http://snap.stanford.edu/jodie/mooc.csv
MTM-1 hand motions	(Rozemberczki et al., 2021)	https://pytorch-geometric-temporal.readthedocs.io/en/latest/notes/introduction.html#benchmark-datasets
Nasdaq	(Duan et al., 2023) and (Chen et al., 2023c)	https://dl.acm.org/doi/10.5555/3172077.3172254 (source paper)
Neonatal EEG	(Fang et al., 2023b)	https://zenodo.org/records/2547147

Table 33
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NOAA weather	(Wang et al., 2023g) and (Li & Tang, 2024)	https://www.ncei.noaa.gov/data/local-climatological-data/
NREL	(Xu et al., 2024), (Marisca et al., 2024) and (Yi et al., 2023)	https://www.nrel.gov/
NYC-Bike	(Ye et al., 2022), (Ma et al., 2024), (Lu & Li, 2020) and (Chen et al., 2023e)	https://citibikenyc.com/system-data
NYC-Taxi	(Yin et al., 2024a), (Yi & Park, 2020), (Ye et al., 2022), (Ma et al., 2024) and (Chen et al., 2023e)	https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page
PAMAP2	(Mondal et al., 2021), (Zhang et al., 2022b) and (Younis & Ahmadi, 2024)	https://archive.ics.uci.edu/dataset/231/pamap2+physical+activity+monitoring
Pedal Me deliveries	(Rozemberczki et al., 2021)	https://pytorch-geometric-temporal.readthedocs.io/en/latest/notes/introduction.html#benchmark-datasets
PeMS03 (PeMSD3)	(Gao et al., 2023c), (Chen et al., 2022e), (Cao et al., 2020) and (Hu et al., 2024a)	https://www.kaggle.com/datasets/elmahy/pems-dataset
PeMS04 (PeMSD4)	(Li et al., 2023j), (Gao et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Zhan et al., 2023), (He et al., 2024c), (Huang et al., 2024a), (Wang et al., 2024g), (Li et al., 2024f), (Yu et al., 2024a), (Chen et al., 2021), (Chen et al., 2022e), (Cao et al., 2020), (Chen et al., 2022d), (Tang et al., 2023b) and (Tang et al., 2023a)	https://www.kaggle.com/datasets/elmahy/pems-dataset
PeMS07 (PeMSD7)	(Cao et al., 2020), (Liu et al., 2022d), (Tang et al., 2023b) and (Tang et al., 2023a)	https://www.kaggle.com/datasets/elmahy/pems-dataset
PeMS08 (PeMSD8)	(Li et al., 2023j), (Gao et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Zhan et al., 2023), (Liang et al., 2024a), (He et al., 2024c), (Huang et al., 2024a), (Wang et al., 2024g), (Li et al., 2024f), (Yu et al., 2024a), (Chen et al., 2021), (Chen et al., 2022e), (Cao et al., 2020), (Chen et al., 2022d), (Wen et al., 2023a), (Tang et al., 2023b) and (Tang et al., 2023a)	https://www.kaggle.com/datasets/elmahy/pems-dataset
PEMS-BAY	(Cini et al., 2023b), (Jin et al., 2023c), (Bloemheuvel et al., 2023a), (Sun et al., 2024a), (Shang et al., 2021), (Yu et al., 2024a), (Fang et al., 2023b), (Wu et al., 2020c), (Cao et al., 2020), (Liu et al., 2022d), (Cini et al., 2023a), (Hu et al., 2024a) and (Oskarsson et al., 2023)	https://zenodo.org/records/4263971
PhysioNet	(Han et al., 2023), (Yalavarthi et al., 2024), (Zhang et al., 2022b) and (Zhang et al., 2024e)	https://archive.physionet.org/challenge/2012/papers/
Reddit network	(Li et al., 2023h)	http://snap.stanford.edu/jodie/reddit.csv
Seattle-loop	(Sun et al., 2024a)	https://github.com/zhiyongc/Seattle-Loop-Data
Sleep-EDF-20	(Ge et al., 2024)	https://gist.github.com/emadeldeen24/a22691e36759934e53984289a94cb09b
Solar-Energy	(Li et al., 2023j), (Gao et al., 2023c), (Jin et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2023c), (Miao et al., 2023), (Sriramulu et al., 2023), (Wang et al., 2022c), (Zhan et al., 2023), (He et al., 2022b), (Wang et al., 2024i), (Li et al., 2024f), (Fang et al., 2023b), (Ye et al., 2022), (Wu et al., 2020c), (Cui et al., 2021), (Cao et al., 2020), (Liu et al., 2022d) and (Liu et al., 2022c)	https://github.com/laiguokun/multivariate-time-series-data
Secure water treatment (SWaT)	(Wang et al., 2024i)	https://itrust.sutd.edu.sg/itrust-labs_datasets/
SHMetro	(Ma et al., 2024)	https://github.com/HCPLab-SYSU/PVCGN/tree/master/data
Stock market data	(Zhang et al., 2023k)	https://www.kaggle.com/datasets/paultimothymooney/stock-market-data
Stocktwits	(Yin et al., 2024a)	https://stocktwits.com/
Synthetic periodic data synthetic	(Oskarsson et al., 2023)	https://github.com/joeloskarsson/tgnn4i
TAIEX	(Chen et al., 2022c)	https://finance.yahoo.com/
Taiwan PM2.5	(Lu & Li, 2020)	https://taqm.epa.gov.tw/taqm/en/default.aspx[†]
TaoBao	(Huang et al., 2021b)	https://tianchi.aliyun.com/competition/entrance/
T-drive	(Liang et al., 2024a)	https://www.kaggle.com/datasets/arashnic/tdriver
Tiingo	(Yin et al., 2024a)	https://www.tiingo.com/
Traffic	(Jin et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2023c), (Miao et al., 2023), (Sriramulu et al., 2023), (Kim et al., 2023c), (Wang et al., 2022c), (He et al., 2022b), (Han et al., 2024a), (Wu et al., 2020c), (Cui et al., 2021), (Liu et al., 2022d), (Huang et al., 2023b), (Yi et al., 2023) and (Liu et al., 2022c)	https://github.com/laiguokun/multivariate-time-series-data
UCI Beijing PM2.5	(Zhang et al., 2023k)	https://archive.ics.uci.edu/ml/datasets/Beijing+PM2.5+Data[†]
UCI human activity recognition	(Wang et al., 2024k) and (Younis & Ahmadi, 2024)	https://archive.ics.uci.edu/dataset/240/human+activity+recognition+using+smartphones
UCR datasets	(Zha et al., 2022)	https://www.cs.ucr.edu/~eamonn/time_series_data_2018/
University of East Anglia (UEA) datasets	(Du et al., 2024), (Gui et al., 2024), (Liu et al., 2024a), (Hong et al., 2025) and (Younis & Ahmadi, 2024)	https://timeseriesclassification.com/
US historical climatology network (USHCN)	(Yalavarthi et al., 2024), (Zhang et al., 2024e) and (Oskarsson et al., 2023)	https://www.osti.gov/biblio/1389426
US stock market price	(Chung et al., 2023)	http://dx.doi.org/10.24963/ijcai.2019/810 (source paper)
Water distribution (WaDi)	(Wang et al., 2024i)	https://itrust.sutd.edu.sg/itrust-labs_datasets/
WESAD dataset	(Shaik et al., 2024)	https://ubi29.informatik.uni-siegen.de/usi/data_wesad.html
Wiki	(Yi et al., 2023)	https://www.kaggle.com/c/web-traffic-time-series-forecasting/data
Wikipedia network	(Li et al., 2023h)	http://snap.stanford.edu/jodie/wikipedia.csv
Windmill	(Rozemberczki et al., 2021)	https://pytorch-geometric-temporal.readthedocs.io/en/latest/notes/introduction.html#benchmark-datasets
Wind-speed	(Zhang et al., 2023j)	https://www.kaggle.com/datasets/fedesoriano/wind-speed-prediction-dataset
Wind generation	(Li et al., 2024f)	https://www.kaggle.com/datasets/sohier/30-years-of-european-wind-generation
WISDM	(Ge et al., 2024) and (Mondal et al., 2021)	https://archive.ics.uci.edu/dataset/507/wisdm+smartphone+and+smartwatch+activity+and+biometrics+dataset

Gui et al. (2024), Hong et al. (2025), Liu et al. (2024a), Younis and Ahmadi (2024).

In general, the data granularity varies significantly, ranging from fractions of seconds to one month, indicating that there is no particular focus on a specific granularity. Individual papers often cover multiple granularities, and many papers take into account datasets with granularity from 5 minutes to 1 day. As for the forecasting horizon, almost all papers focus on multi-step forecasting, usually considering 12 different forecasting horizons at the same time. Only a few papers mention data pre-processing, and usually utilize min-max or Z-score normalization.

5.7.3. Types of models

Among the 77 papers in the "Generic" thematic group, 56 use a purely convolutional GNN approach, and 10 employ a purely attentional model. Five paper lack sufficient detail to be classified within the taxonomy chosen (Du et al., 2024; Gui et al., 2024; Hong et al., 2025; Kim et al., 2023c; Liu et al., 2024a), and another one declares that it uses an aggregating approach that is simpler than either convolutional or attentional approaches (Miao et al., 2023). Moreover, Cini et al. (2023a) use an approach that can be proved to be equivalent to a convolutional model; Cini et al. (2023a) perform a general analysis that extends beyond a single model; Rozemberczki et al. (2021) explore various models, all based on convolutional architectures; Oskarsson et al. (2023) propose an architecture that can adopt either a convolutional or an attentional aggregation. Another paper proposes a so-called multivariate time series with dynamic graph neural ordinary differential equations (MTGODE) model, where the continuous dynamics of simplified graph propagation is described by an ordinary differential equation (ODE) (Jin et al., 2023c). This is not the only paper in this section using differential equations. In Sun et al. (2024a), two domain specific ODEs (one for traffic speed evolution, and the other for disease propagation) are integrated into the convolutional GNN model. The authors argue that this dynamics-informed model approach enhances robustness, allow easier generalization when the equation of the dynamics is known, and reduces the number of model parameters. Additionally, during inference, the model only requires a single data point, as the ODEs explicitly incorporate the immediate dynamics.

As for the definition of the graph structure, the majority of these models use self-learning techniques. This is a straightforward choice, since all the papers in this group want to ensure the applicability of the model in different contexts, and the use of pre-defined rules for the definition of the graph limits the model's universal applicability and negatively impacts knowledge transfer. More than half of the papers employ a dynamic graph structure, which adapts to the varying temporal patterns observed in the data.

Yi et al. (2023) introduce a novel data structure called hypervariate graph, where each time serie values is represented as a graph node, and slicing windows are modeled as fully connected space-time graphs. Unlike traditional approaches that treat spatial and temporal aspects separately, according to the authors, this approach captures spatiotemporal correlations in an integrated manner.

The two most commonly utilized loss functions are the MSE and the MAE. Since the graph structure is typically learned by the models themselves, many papers include a regularization term in the loss function for the optimization of the graph structure (e.g., Chen & Xie, 2022; Guo et al., 2023a; Li et al., 2023j,k; Shang et al., 2021).

The majority of the papers specify the language and libraries used for the code, namely Python with PyTorch, PyTorch Geometric (Fey & Lenssen, 2019), and Torch Spatiotemporal (Cini and Marisca, 2022). However, only slightly more than half of the papers provide a link to the source code. The links to the code repositories are listed in Table 34. Cini et al. (2023a) do not introduce a new model but rather investigate the relationship between global and local patterns in graph-based spatiotemporal forecasting. The authors provide access to their source code at https://github.com/Graph-Machine-Learning-Group/taming-local-effects-stgnns. Additionally, this group includes the work that introduced the PyTorch Geometric Temporal library (Rozemberczki et al., 2021), a framework for dynamic graph learning. The corresponding source code is publicly available at https://github.com/benedekrozemberczki/pytorch_geometric_temporal. In addition, the authors compare various open-source libraries for geometric deep learning.

5.7.4. Benchmark models

Table 35 displays the benchmark models utilized by at least two of the selected "Generic" papers.

This "Generic" thematic group includes a wide variety of benchmark models, also due to the large number of papers within this group. As for mathematical and statistical models, autoregressions and ARIMA models are very popular for their simplicity and interpretability. Among non-GNN machine learning models, the most widely used models are LSTM networks, the so-called temporal pattern attention long-short term memory network (TPA-LSTM) (Shih et al., 2019), and the long-short term time series network (LSTNet) (Lai et al., 2018). The TPA-LSTM model employs a set of filters to capture time-invariant temporal patterns, and an attention mechanism to identify relevant time series for multivariate forecasting. The source code for this benchmark model is available at https://github.com/gantheory/TPA-LSTM. The LSTNet model combines a convolution neural network and a recurrent neural network to capture short-term local dependencies among variables and identify long-term patterns. Additionally, it incorporates an autoregressive model that enhances the robustness of the deep learning approach to time series with significant scale fluctuations. The source code for the model is accessible at https://github.com/laiguokun/LSTNet. Among GNN models, the most common ones are DCRNN (Li et al., 2018), MT-GNN (Wu et al., 2020c), and GWN (Wu et al., 2019) models, already discussed in the previous subsections.

5.7.5. Results

The most common error metrics used in the evaluation of the models in the "Generic" group are, in order, the mean absolute error (MAE), correlation coefficient (CORR), root mean squared error (RMSE), root relative squared error (RRSE), mean absolute percentage error (MAPE), and mean squared error (MSE). Differently from other metrics, where lower values indicate higher accuracy, the correlation coefficient (CORR) quantifies the strength of the linear relationship between predicted and actual values, with higher values indicating a better performance. This subsection about results compares the results obtained for the Electricity consumption, Exchange rate, Solar energy and Traffic datasets. The results of the proposed models and benchmarks on the "Mobility" datasets were already reported with a * in Subsection 5.5.5.

Table 36 shows the accuracy of the various models applied to the Electricity consumption dataset, which includes data from 1st January 2012 to 31st December 2014 at hourly granularity, for 3, 6, 12 and 24 steps ahead horizons. The accuracy is expressed in terms of RRSE and CORR.

The accuracy of the various models varies depending on the studied forecasting horizon but, overall, one can notice that the GNN models perform better than the others, with the static and dynamic graph learning network (SDGL) (Li et al., 2023k) and the temporal polynomial graph neural network (TPGNN) (Liu et al., 2022d) being the most accurate. The SDGL model first employs a static and dynamic graph learning module that incorporates graph regularization to control the smoothness, connectivity, and sparsity of the learned graph. The graph input then passes through gated temporal convolutional networks and graph convolution modules, which are equipped with residual and skip connections that deliver the information to the output layer. The TPGNN builds a series of matrix polynomials that share a common matrix basis. The graph learning module first captures the overall correlations using a static matrix basis. Then, a set of time-varying coefficients and the matrix basis are used to create a dynamic graph. Overall, the TPGNN

Table 34
List of source codes of the "Generic" models in the review.

Model	Link
Adaptive dependency learning neural network (ADLNN) (Sriramulu et al., 2023)	https://github.com/AbishekSriramulu/ADLGNN.git†
Attention-adjusted graph spatio-temporal network (AGSTN) (Lu & Li, 2020)	https://github.com/l852888/AGSTN
Cross-attention temporal dynamic graph neural network (CATodyNet) (Gui et al., 2024)	https://github.com/HQYWY/CATodyNet
Graph neural network with neural Granger causality (CauGNN) (Duan et al., 2023)	https://github.com/RRRussell/CauGNN
Spatio-temporal contrastive learning (CL4ST) (Tang et al., 2023a)	https://github.com/HKUDS/CL4ST
CrossGNN (Huang et al., 2023b)	https://github.com/hqh0728/CrossGNN
Dynamic diffusion-variational GNN (DVGNN) (Liang et al., 2024a)	https://github.com/gorgen2020/DVGNN
Evolving multi-scale graph neural network (ESG) (Ye et al., 2022)	https://github.com/LiuZH-19/ESG
Fourier graph neural network (FourierGNN) (Yi et al., 2023)	https://github.com/aikunyi/FourierGNN
Graph interpolation attention recursive network (GinAR) (Yu et al., 2024a)	https://github.com/ChengqingYu/GinAR
Gformer (Wang et al., 2023g)	https://github.com/wxh453751461/Gformer
Graphs for forecasting irregularly sampled time series with missing values (GraFITi) (Yalavarthi et al., 2024)	https://github.com/yalavarthivk/GraFITi
GraphSensor (Ge et al., 2024)	https://github.com/jldx-gjq/Graphnet/tree/main/graphsensor-code-main
Graph for time series (GTS) (Shang et al., 2021)	https://github.com/chaoshangcs/GTS
HAR-Sensor (Mondal et al., 2021)	https://github.com/riktimmondal/HAR-Sensor†
Hierarchical downsampling time-then-space (HD-TTS) (Marisca et al., 2024)	https://github.com/marshka/hdtts
HyperTime (Younis & Ahmadi, 2024)	https://gitfront.io/r/user-9180183/WXPgc7aQjSKE/HyperTime/†
Multi-scale adaptive graph neural network (MAGNN) (Chen et al., 2023c)	https://github.com/shangzongjiang/MAGNN
Multi-task dynamic graph generation framework for multivariate time series forecasting (MDG) (Huang et al., 2024a)	https://github.com/gortwwh/MDG
Multivariate time series deep spatiotemporal forecasting model with a graph neural network (MDST-GNN) (He et al., 2022b)	https://github.com/yiminghzc/MDST-GNN
Multivariate time series classification based on fusion features (MSTC_FF) (Du et al., 2024)	https://github.com/dumingsen/MTSC_FF
Multivariate time series forecasting with graph neural networks (MTGNN) (Wu et al., 2020c)	https://github.com/nnzhan/MTGNN
Multivariate time series with dynamic graph neural ordinary differential equations (MTGODE) (Jin et al., 2023c)	https://github.com/GRAND-Lab/MTGODE
RAINDROP (Zhang et al., 2022b)	https://github.com/mims-harvard/Raindrop
Static and dynamic graph learning network (SDGL) (Li et al., 2023k)	https://github.com/ZhuoLinLi-shu/SDGL
Similarity-aware time-series classification (SimTSC) (Zha et al., 2022)	https://github.com/daochenzha/SimTSC
Sparse graph learning from spatiotemporal time series (Cini et al., 2023b)	https://github.com/andreacini/sparse-graph-learning
Spatial relation decomposition (SRD) (Fang et al., 2023b)	https://github.com/Arthur-Null/SRD/tree/main
Spatio-temporal graph neural networks (STExplainer) (Tang et al., 2023b)	https://github.com/HKUDS/STExplainer
Time-aware multipersistence spatio-supra graph convolutional network (TAMP-S2GCNet) (Chen et al., 2022e)	https://www.dropbox.com/sh/n0ajd5l0tdeyb80/AABGn-ejfV1YtRwjf_L0AOsNa?dl=0
Temporal decomposition enhanced graph neural network for multivariate time series forecasting (TDG4MSF) (Miao et al., 2023)	https://github.com/TYUT-Theta/MHZN.git
Temporal graph convolution and attention (T-GAN) (Huang et al., 2021b)	https://github.com/malei666666/T_GAN
Temporal graph neural networks for irregular data (TGNN4I) (Oskarsson et al., 2023)	https://github.com/joeloskarsson/tgnn4i
Temporal dynamic graph neural network (TodyNet) (Liu et al., 2024a)	https://github.com/liuxz1011/TodyNet
Transformable patching graph neural network (T-PATCHGNN) (Zhang et al., 2024e)	https://github.com/usail-hkust/t-PatchGNN
Temporal polynomial graph neural network (TPGNN) (Liu et al., 2022d)	https://github.com/zyplanet/TPGNN
Two GNN models with different graph structures (Bloemheuvel et al., 2023a)	https://github.com/StefanBloemheuvel/graph_comparison
Unified Spatio-Temporal Diffusion Models (USTD) (Hu et al., 2024a)	https://github.com/hjf1997/USTD
Weight-bounded-GAT (Zhang et al., 2023k)	https://github.com/zzh237/Weight-bounded-GAT
Zigzag filtration curve based supra-hodge convolution networks (ZFC-SHCN) (Chen et al., 2022d)	https://github.com/zfcshcn/ZFC-SHCN
Time zigzags at graph convolutional network (Z-GCNET) (Chen et al., 2021)	https://github.com/Z-GCNETs/Z-GCNETs

model uses an encoder-decoder architecture and makes predictions in an auto-regressive manner.

Table 37 presents the accuracy of different models applied to the Exchange rate dataset, with daily data from 1990 to 2016. The evaluation covers horizons of 3, 6, 12, and 24 steps ahead, with accuracy measured by RRSE and CORR.

Also in this case, GNN models are the best. The so-called discrete graph structure learning for time series model (GTS), proposed in 2021 by Shang et al. (2021) for traffic and sensor network forecasting, and used as a benchmark by Li et al. (2023k), demonstrates itself to have a superior performance. It includes a probabilistic graph learning module that optimizes the mean performance over the graph distribution, and a recurrent graph convolutional module to generate the forecasts.

Table 38 summarizes the accuracy of the various models on the Solar energy dataset, covering the period from January 1, 2016, to December 31, 2016, at 10-minutes intervals. The analysis considers forecasting horizons of 3, 6, 12, and 24 steps ahead, and the results are expressed in terms of RRSE and CORR.

The results indicate that the dynamic spatiotemporal interactive graph neural network (DSTIGNN) model (Gao et al., 2023c) is the most accurate on the solar energy dataset. The DSTIGNN model employs a hierarchical structure consisting of a spatio-temporal interactive learning module, a dynamic graph inference module, multiple spatio-temporal layers, and an output module. The spatio-temporal interactive learning module splits the time series into two subsequences to capture both temporal and spatial correlations. Then, the graph inference module learns a dynamic adjacency matrix for the graph. Once the graph structure is determined, a stack of graph convolutional layers, enhanced with residual connections, along with a convolutional output module, generate the final forecast.

Finally, Table 39 illustrates the performance of different models on the Traffic dataset, with hourly data between 2015 and 2016. The accuracy of each model is assessed across 3, 6, 12, and 24 steps ahead horizons, with RRSE and CORR as the evaluation metrics.

The accuracy of the models varies by horizon and metric. Overall, the best models are the temporal polynomial graph neural network (TPGNN) (Liu et al., 2022d) already discussed for the Electricity consumption dataset, and the temporal decomposition enhanced graph neural network for multivariate time series forecasting (TDG4-MSF) (Miao

Table 35
List of benchmark models in the "Generic" group divided per category.

Category	Model	Used in
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	(Li et al., 2023j), (Gao et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2023c), (Miao et al., 2023), (Sriramulu et al., 2023), (Chen et al., 2022c), (Zhan et al., 2023), (Chung et al., 2023), (Li & Tang, 2024), (Huang et al., 2024a), (Wang et al., 2024g), (Li et al., 2024f), (Yi & Park, 2020), (Shang et al., 2021), (Fang et al., 2023b), (Ye et al., 2022), (Lu & Li, 2020), (Wu et al., 2020c), (Cui et al., 2021), (Liu et al., 2022d) and (Chen et al., 2023e)
	Gaussian process (GP)	(Li et al., 2023j), (Gao et al., 2023c), (Li et al., 2023k), (Chen et al., 2023c), (Miao et al., 2023), (Sriramulu et al., 2023), (Fang et al., 2023b), (Ye et al., 2022), (Wu et al., 2020c), (Cui et al., 2021) and (Liu et al., 2022d)
	Historical average (HA)	(Li et al., 2023k), (Zhan et al., 2023), (Wang et al., 2024g), (Shang et al., 2021), (Ma et al., 2024), (Cui et al., 2021), (Chen et al., 2021), (Tang et al., 2023b) and (Tang et al., 2023a)
	Vector autoregression (VAR)	(Li et al., 2023j), (Gao et al., 2023c), (Duan et al., 2023), (Li et al., 2023k), (Guo et al., 2023a), (Miao et al., 2023), (Chen et al., 2022c), (Zhan et al., 2023), (Wang et al., 2024g), (Li et al., 2024f), (Xu et al., 2024), (Shang et al., 2021), (Chen et al., 2021), (Yi et al., 2023), (Su et al., 2021), (Tang et al., 2023b) and (Tang et al., 2023a)
Non-GNN machine learning methods	Autoformer (Wu et al., 2021)	(Gao et al., 2023c), (Zhang et al., 2023j), (Kim et al., 2023c), (Xu et al., 2024), (Fang et al., 2023b), (Huang et al., 2023b) and (Yi et al., 2023)
	Crossformer (Zhang & Yan, 2023)	(Gao et al., 2023c), (Zhang et al., 2024e) and (Huang et al., 2023b)
	DeepAR (Salinas et al., 2020)	(Chen et al., 2023b), (Li & Tang, 2024) and (Wen et al., 2023a)
	Attentive hierarchical recurrent networks for crime prediction (DeepCrime) (Huang et al., 2018)	(Tang et al., 2023b) and (Tang et al., 2023a)
	DeepGLO (Rajat et al., 2019)	(Xu et al., 2024), (Chen et al., 2022e), (Cao et al., 2020), (Chen et al., 2022d), (Yi et al., 2023) and (Chen et al., 2023e)
	DeepSleepNet (Supratak et al., 2017)	(Ge et al., 2024) and (Wang et al., 2024k)
	DeepState (Rangapuram et al., 2018)	(Chen et al., 2022e), (Cao et al., 2020), (Chen et al., 2022d) and (Chen et al., 2023e)
	DLinear (Zeng et al., 2023)	(Zhang et al., 2023j), (Yalavarthi et al., 2024), (Zhang et al., 2024e) and (Huang et al., 2023b)
	Deep multi-view spatial-temporal network (DMVST-Net) (Yao et al., 2018)	(Yi & Park, 2020) and (Chen et al., 2023e)
	Dual self-attention network for multi-variate time series forecasting (DSANet) (Huang et al., 2019)	(Li et al., 2023j), (Li et al., 2023k), (Li et al., 2024f), (Chen et al., 2021) and (Tang et al., 2023a)
	Exponential smoothing transformers for time-series forecasting (ETSformer) (Woo et al., 2022)	(Zhang et al., 2023j) and (Huang et al., 2023b)
	Frequency enhanced decomposed trans-former (FEDformer) (Zhou et al., 2022)	(Gao et al., 2023c), (Xu et al., 2024), (Yalavarthi et al., 2024) and (Huang et al., 2023b)
	Feed-forward neural network (FNN)	(Chen et al., 2022c), (Chung et al., 2023), (Yi & Park, 2020), (Shang et al., 2021) and (Zha et al., 2022)
	Gated recurrent unit (GRU)	(Li et al., 2023j), (Li et al., 2023k), (Wang et al., 2023g), (Zhan et al., 2023), (He et al., 2022b), (Yin et al., 2024a), (Shaik et al., 2024), (Li et al., 2024f), (Marisca et al., 2024), (Zhang et al., 2022b), (Zhang et al., 2024e), (Chen et al., 2021), (Yalavarthi et al., 2024), (Su et al., 2021) and (Oskarsson et al., 2023)
	Hybrid framework based on fully Dilated CNN (HyDCNN) (Li et al., 2021f)	(Jin et al., 2023c) and (Sriramulu et al., 2023)
	InceptionTime (Ismail Fawaz et al., 2020)	(Fang et al., 2023b) and (Zha et al., 2022)
	Informer (Zhou et al., 2021)	(Gao et al., 2023c), (Zhang et al., 2023j), (Wang et al., 2023g), (Kim et al., 2023c), (Huang et al., 2024a), (Xu et al., 2024), (Yalavarthi et al., 2024), (Ma et al., 2024), (Cui et al., 2021), (Liu et al., 2022d), (Yi et al., 2023) and (Su et al., 2021)
	k-nearest neighbors (KNN)	(Chen et al., 2022c), (Wang et al., 2024i), (Younis & Ahmadi, 2024) and (Zha et al., 2022)
	LogTrans (Nie et al., 2022)	(Wang et al., 2023g) and (Kim et al., 2023c)
	Long-short term memory network (LSTM)	(Han et al., 2023), (Gao et al., 2023c), (Guo et al., 2023a), (Wang et al., 2023g), (Chen et al., 2022c), (Kim et al., 2023c), (Chen & Xie, 2022), (Zhan et al., 2023), (Chung et al., 2023), (He et al., 2024c), (Huang et al., 2024a), (Yin et al., 2024a), (Wang et al., 2024g), (Shang et al., 2021), (Yalavarthi et al., 2024), (Ma et al., 2024), (Lu & Li, 2020), (Chen et al., 2021), (Chen et al., 2022e), (Cao et al., 2020), (Liu et al., 2022d), (Chen et al., 2022d), (Su et al., 2021) and (Chen et al., 2023e)
	Long-short term time series network (LST-Net) (Lai et al., 2018)	(Li et al., 2023j), (Gao et al., 2023c), (Jin et al., 2023c), (Duan et al., 2023), (Li et al., 2023k), (Chen et al., 2023c), (Miao et al., 2023), (Wang et al., 2023g), (Sriramulu et al., 2023), (Kim et al., 2023c), (Wang et al., 2022c), (Chung et al., 2023), (He et al., 2022b), (Wang et al., 2024i), (Li & Tang, 2024), (Xu et al., 2024), (Fang et al., 2023b), (Ye et al., 2022), (Wu et al., 2020c), (Cui et al., 2021), (Chen et al., 2022e), (Cao et al., 2020), (Liu et al., 2022d), (Chen et al., 2022d), (Yi et al., 2023), (Su et al., 2021), (Chen et al., 2023e) and (Liu et al., 2022c)
	Multi-level construal neural network (ML-CNN) (Cheng et al., 2020)	(Duan et al., 2023) and (Wang et al., 2022c)
	Multi-time attention networks (mTANs) (Shukla & Marlin, 2021)	(Yalavarthi et al., 2024), (Zhang et al., 2022b) and (Zhang et al., 2024e)
	Neural basis expansion analysis for inter-pretable time series forecasting (N-BEATS) (Oreshkin et al., 2020)	(Chen et al., 2023b), (Kim et al., 2023c), (Chen et al., 2022e), (Cao et al., 2020), (Chen et al., 2022d) and (Chen et al., 2023e)
	Channel-independent patch time series Transformer (PatchTST) (Nie et al., 2023)	(Zhang et al., 2024e) and (Huang et al., 2023b)

Table 35
Continued

	Reformer (Kitaev et al., 2020)	(Zhang et al., 2023j), (Wang et al., 2023g), (Kim et al., 2023c), (Xu et al., 2024) and (Yi et al., 2023)
	Recurrent neural network (RNN)	(Chung et al., 2023) and (Cini et al., 2023a)
	Recurrent neural network with fully connected gated recurrent units (RNN-GRU)	(Li et al., 2023j), (Duan et al., 2023), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2023c), (Miao et al., 2023), (Sriramulu et al., 2023), (Wang et al., 2022c), (Li et al., 2024f), (Ye et al., 2022), (Wu et al., 2020c) and (Liu et al., 2022d)
	Rocket (Dempster et al., 2020)	(Hong et al., 2025) and (Fang et al., 2023b)
	SCINet (Liu et al., 2022b)	(Gao et al., 2023c) and (He et al., 2022b)
	Set functions for time series (SeFT) (Horn et al., 2020)	(Zhang et al., 2022b) and (Zhang et al., 2024e)
	State frequency memory (SFM) (Zhang et al., 2017c)	(Xu et al., 2024), (Chen et al., 2022e), (Cao et al., 2020), (Chen et al., 2022d) and (Yi et al., 2023)
	Shapelet-neural network (ShapeNet) (Li et al., 2021b)	(Gui et al., 2024), (Liu et al., 2024a) and (Younis & Ahmadi, 2024)
	Spatial-temporal dynamic network (STDN) (Yao et al., 2019)	(Yi & Park, 2020), (Tang et al., 2023b), (Chen et al., 2023e) and (Tang et al., 2023a)
	Spatial-temporal identity (STID) (Shao et al., 2022a)	(Gao et al., 2023c) and (Yu et al., 2024a)
	Spatial-temporal transformer network (STtrans) (Wu et al., 2020a)	(Tang et al., 2023b) and (Tang et al., 2023a)
	Spatio-temporal residual networks (ST-ResNet) (Zhang et al., 2017b)	(Tang et al., 2023b), (Chen et al., 2023e) and (Tang et al., 2023a)
	Support vector machine (SVM)	(Chen et al., 2022c), (He et al., 2024c), (Shang et al., 2021), (Lu & Li, 2020), (Chen et al., 2023e) and (Tang et al., 2023a)
	TapNet (Zhang et al., 2020b)	(Du et al., 2024), (Liu et al., 2024a), (Younis & Ahmadi, 2024) and (Zha et al., 2022)
	Temporal convolutional network (TCN) (Bai et al., 2018)	(Zhan et al., 2023), (Wang et al., 2024i), (He et al., 2024c), (Huang et al., 2024a), (Xu et al., 2024), (Chen et al., 2022e), (Cao et al., 2020), (Chen et al., 2022d), (Yi et al., 2023) and (Chen et al., 2023e)
	Temporal 2D-variation modeling for general time series analysis (TimesNet) (Wu et al., 2023a)	(Zhang et al., 2023j), (Zhang et al., 2024e), (Younis & Ahmadi, 2024) and (Huang et al., 2023b)
	Temporal pattern attention long-short term memory network (TPA-LSTM) (Shih et al., 2019)	(Li et al., 2023j), (Gao et al., 2023c), (Jin et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2023c), (Miao et al., 2023), (Sriramulu et al., 2023), (He et al., 2022b), (Li et al., 2024f), (Ye et al., 2022), (Wu et al., 2020c), (Cui et al., 2021), (Liu et al., 2022d) and (Liu et al., 2022c)
	TimeGrad (Rasul et al., 2021)	(Hu et al., 2024a) and (Wen et al., 2023a)
	Transformer (Vaswani et al., 2017)	(Han et al., 2023), (Duan et al., 2023), (Li & Tang, 2024), (Zhang et al., 2022b) and (Oskarsson et al., 2023)
	Hybrid of the multilayer perception and autoregressive model (VAR-MLP) (Zhang, 2003)	(Li et al., 2023j), (Gao et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2023c), (Miao et al., 2023), (Sriramulu et al., 2023), (Wang et al., 2022c), (He et al., 2022b), (Li et al., 2024f), (Ye et al., 2022), (Wu et al., 2020c), (Cui et al., 2021), (Liu et al., 2022d) and (Liu et al., 2022c)
	WEASEL + multivariate unsupervised symbols and derivatives (WEASEL+MUSE) (Schäfer & Leser, 2017)	(Du et al., 2024), (Gui et al., 2024), (Liu et al., 2024a) and (Younis & Ahmadi, 2024)
	Extreme gradient boosting (XGBoost)	(Yi & Park, 2020), (Ye et al., 2022) and (Ma et al., 2024)
GNN methods	Adaptive graph convolutional recurrent network (AGCRN) (Bai et al., 2020)	(Li et al., 2023j), (Gao et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2023c), (Zhan et al., 2023), (He et al., 2024c), (Wang et al., 2024g), (Xu et al., 2024), (Marisca et al., 2024), (Ma et al., 2024), (Chen et al., 2021), (Chen et al., 2022e), (Chen et al., 2022d), (Yi et al., 2023), (Cini et al., 2023a), (Tang et al., 2023b), (Chen et al., 2023e), (Rozemberczki et al., 2021) and (Tang et al., 2023a)
	Attention-based spatial-temporal graph convolutional network (ASTGCN) (Guo et al., 2019)	(Li et al., 2023k), (Guo et al., 2023a), (Liang et al., 2024a), (He et al., 2024c), (Huang et al., 2024a), (Wang et al., 2024g), (Lu & Li, 2020), (Chen et al., 2021), (Tang et al., 2023b), (Zhang et al., 2023k) and (Tang et al., 2023a)
	Attention based spatial-temporal graph neural network (ASTGNN) (Guo et al., 2022a)	(Gao et al., 2023c) and (He et al., 2024c)
	Coupled layer-wise convolutional recurrent neural network (CCRNN) (Ye et al., 2021)	(Ye et al., 2022) and (Ma et al., 2024)
	CrossGNN (Huang et al., 2023b)	(Zhang et al., 2024e) and (Huang et al., 2023b)
	Diffusion convolutional recurrent neural network (DCRNN) (Li et al., 2018)	(Li et al., 2023j), (Gao et al., 2023c), (Jin et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2022c), (Chen & Xie, 2022), (Wang et al., 2022c), (Zhan et al., 2023), (Liang et al., 2024a), (He et al., 2024c), (Huang et al., 2024a), (Wang et al., 2024g), (Li et al., 2024f), (Shang et al., 2021), (Marisca et al., 2024), (Fang et al., 2023b), (Ye et al., 2022), (Ma et al., 2024), (Lu & Li, 2020), (Wu et al., 2020c), (Chen et al., 2021), (Chen et al., 2022e), (Liu et al., 2022d), (Chen et al., 2022d), (Cini et al., 2023a), (Hu et al., 2024a), (Wen et al., 2023a), (Tang et al., 2023b), (Chen et al., 2023e), (Rozemberczki et al., 2021) and (Tang et al., 2023a)
	Dynamic graph convolutional recurrent network (DGCRN) (Li et al., 2023b)	(Huang et al., 2024a) and (Yin et al., 2024a)
	Dynamic and multi-faceted spatiotemporal graph convolution network (DMSTGCN) (Han et al., 2021)	(He et al., 2024c), (Yang et al., 2024b), (Fang et al., 2023b), (Tang et al., 2023b) and (Tang et al., 2023a)
	Dynamic spatial-temporal aware graph neural network (DSTAGNN) (Lan et al., 2022)	(Liang et al., 2024a) and (Tang et al., 2023b)

Table 35
Continued

Evolving multi-scale graph neural network (ESG) (Ye et al., 2022)	(Gao et al., 2023c) and (Ma et al., 2024)
Graph auto encoder (GAE) (Kipf et al., 2018)	(Li et al., 2023h) and (Huang et al., 2021b)
Graph deviation network (GDN) (Deng & Hooi, 2021)	(Wang et al., 2024i) and (Zhang et al., 2023k)
Graph multi-attention network (GMAN) (Zheng et al., 2020)	(Li et al., 2023j), (Jin et al., 2023c), (Chen & Xie, 2022), (Zhan et al., 2023), (Wu et al., 2020c), (Tang et al., 2023b), (Zhang et al., 2023k) and (Tang et al., 2023a)
Graph-based multi-step dependency relation (GMSDR) (Liu et al., 2022a)	(Hu et al., 2024a), (Wen et al., 2023a), (Tang et al., 2023b) and (Tang et al., 2023a)
Discrete graph structure learning for time series (GTS) (Shang et al., 2021)	(Cini et al., 2023b), (Li et al., 2023k), (Huang et al., 2024a), (Sun et al., 2024a), (Ye et al., 2022) and (Ma et al., 2024)
Graph WaveNet (GWN) (Wu et al., 2019)	(Gao et al., 2023c), (Jin et al., 2023c), (Guo et al., 2023a), (Chen et al., 2023c), (Chen & Xie, 2022), (Wang et al., 2022c), (He et al., 2024c), (Huang et al., 2024a), (Yang et al., 2024b), (Xu et al., 2024), (Marisca et al., 2024), (Zhang et al., 2024e), (Ma et al., 2024), (Wu et al., 2020c), (Chen et al., 2021), (Chen et al., 2022e), (Cao et al., 2020), (Liu et al., 2022d), (Chen et al., 2022d), (Yi et al., 2023), (Cini et al., 2023a), (Hu et al., 2024a), (Tang et al., 2023b), (Chen et al., 2023e) and (Tang et al., 2023a)
Hypergraph convolutional recurrent neural network (HGC-RNN) (Yi & Park, 2020)	(Wang et al., 2024g) and (Chen et al., 2023e)
Long short-term graph convolutional networks (LSGCN) (Huang et al., 2021a)	(Chen et al., 2021) and (Tang et al., 2023a)
Multi-range attentive bicomponent graph convolutional network (MRA-BGCN) (Chen et al., 2020c)	(Chen & Xie, 2022) and (Wu et al., 2020c)
Multivariate time series forecasting with graph neural network (MTGNN) (Wu et al., 2020c)	(Cini et al., 2023b), (Li et al., 2023j), (Gao et al., 2023c), (Jin et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2023c), (Miao et al., 2023), (Sriramulu et al., 2023), (Chen & Xie, 2022), (Wang et al., 2022c), (Zhan et al., 2023), (He et al., 2022b), (Li & Tang, 2024), (He et al., 2024c), (Huang et al., 2024a), (Sun et al., 2024a), (Li et al., 2024f), (Yang et al., 2024b), (Xu et al., 2024), (Zhang et al., 2024e), (Fang et al., 2023b), (Ye et al., 2022), (Cui et al., 2021), (Liu et al., 2022d), (Huang et al., 2023b), (Yi et al., 2023), (Liu et al., 2022c) and (Zhang et al., 2023k)
Multivariate time series with dynamic graph neural ordinary differential equations (MTGODE) (Jin et al., 2023c)	(Zhan et al., 2023), (Sun et al., 2024a) and (Yang et al., 2024b)
Node2vec (Grover & Leskovec, 2016)	(Li et al., 2023h) and (Huang et al., 2021b)
Spectral temporal graph neural network for multivariate time-series forecasting (StemGNN) (Cao et al., 2020)	(Huang et al., 2024a), (Li et al., 2024f), (Xu et al., 2024), (Zhang et al., 2024e), (Ye et al., 2022), (Chen et al., 2022e), (Cao et al., 2020), (Liu et al., 2022d), (Chen et al., 2022d), (Yi et al., 2023), (Tang et al., 2023b), (Chen et al., 2023e) and (Tang et al., 2023a)
Spatial-temporal fusion graph neural network (STFGNN) (Li & Zhu, 2021)	(Li et al., 2023j), (Chen & Xie, 2022), (Li et al., 2024f), (Tang et al., 2023b) and (Tang et al., 2023a)
Spatio-temporal graph convolutional network (STGCN) (Yu et al., 2018)	(Li et al., 2023j), (Jin et al., 2023c), (Li et al., 2023k), (Guo et al., 2023a), (Chen et al., 2022c), (Chen & Xie, 2022), (Zhan et al., 2023), (Huang et al., 2024a), (Wang et al., 2024g), (Sun et al., 2024a), (Ye et al., 2022), (Wu et al., 2020c), (Chen et al., 2021), (Chen et al., 2022e), (Cao et al., 2020), (Liu et al., 2022d), (Chen et al., 2022d), (Hu et al., 2024a), (Wen et al., 2023a), (Tang et al., 2023b), (Chen et al., 2023e), (Zhang et al., 2023k) and (Tang et al., 2023a)
Spatio-temporal graph neural controlled differential equation (STG-NCDE) (Choi et al., 2022)	(Jin et al., 2023c), (Hu et al., 2024a), (Wen et al., 2023a), (Tang et al., 2023b) and (Tang et al., 2023a)
Spatial-temporal graph ODE networks (STGODE) (Fang et al., 2021)	(Jin et al., 2023c), (Zhan et al., 2023), (Liang et al., 2024a), (Hu et al., 2024a), (Tang et al., 2023b) and (Tang et al., 2023a)
Deep-meta-learning based model (ST-MetaNet) (Pan et al., 2019)	(Chen & Xie, 2022), (Wu et al., 2020c), (Tang et al., 2023b), (Chen et al., 2023e) and (Tang et al., 2023a)
Spatiotemporal multi-graph convolution network (ST-MGCN) (Geng et al., 2019)	(Lu & Li, 2020) and (Chen et al., 2023e)
Spatio-temporal synchronous graph convolutional network (STSGCN) (Song et al., 2020a)	(Li et al., 2023j), (Gao et al., 2023c), (Li et al., 2023k), (Wang et al., 2024i), (Huang et al., 2024a), (Wang et al., 2024g), (Li et al., 2024f), (Ye et al., 2022), (Chen et al., 2021), (Hu et al., 2024a), (Tang et al., 2023b) and (Tang et al., 2023a)
Spatial-temporal sequential hypergraph network (ST-SHN) (Xia et al., 2021a)	(Tang et al., 2023b) and (Tang et al., 2023a)
Time-aware multipersistence spatio-supra graph convolutional network (TAMP-S2GCNet) (Chen et al., 2022e)	(Tang et al., 2023b) and (Tang et al., 2023a)
Temporal graph convolutional network (T-GCN) (Zhao et al., 2020b)	(Liang et al., 2024a), (Li & Tang, 2024) and (Rozemberczki et al., 2021)
Temporal dynamic graph neural network (TodyNet) (Liu et al., 2024a)	(Gui et al., 2024), (Hong et al., 2025) and (Younis & Ahmadi, 2024)
Time zigzags at graph convolutional networks for time series forecasting (Z-GCNETs) (Chen et al., 2021)	(Wang et al., 2024g), (Li et al., 2024f), (Chen et al., 2022e), (Cao et al., 2020), (Chen et al., 2022d), (Tang et al., 2023b), (Chen et al., 2023e) and (Tang et al., 2023a)

Table 36
Comparison of the average accuracy of the different models on the Electricity consumption dataset for 3, 6, 12, and 24 steps time horizons, expressed in terms of RRSE and CORR. The numbers corresponding to the highest accuracy are underlined.

Time horizon	3 steps		6 steps		12 steps		24 steps	
Metrics	RRSE	CORR	RRSE	CORR	RRSE	CORR	RRSE	CORR
ADLGNN (Sriramulu et al., 2023)	0.0719	0.9506	0.0809	0.9386	0.0887	0.9312	0.0930	0.9294
AGCRN	0.0766	0.9408	0.0894	0.9309	0.0921	0.9222	0.0967	0.9183
AGLG-GRU (Guo et al., 2023a)	0.0738	0.9434	0.0864	0.9302	0.0912	0.9283	0.0947	0.9274
AR	0.0995	0.8845	0.1035	0.8632	0.1050	0.8591	0.1054	0.8595
ARIMA	0.0917	0.8902	0.1002	0.8834	0.1028	0.8604	0.1042	0.8487
Autoformer	0.1258	0.9147	0.1344	0.9001	0.1357	0.8921	0.1554	0.8704
Crossformer	0.0742	0.9452	0.0855	0.9351	0.0901	0.9280	0.0967	0.9205
DPGNN (Li et al., 2024f)	0.0720	0.9527	0.0810	0.9422	0.0893	0.9357	0.0935	0.9291
DSTGN (Li et al., 2023j)	0.0713	0.9518	0.0821	0.9424	0.0887	0.9357	-	-
DSTIGNN (Gao et al., 2023c)	0.0733	0.9515	0.0820	0.9412	0.0899	0.9338	0.0954	0.9289
ESG (Ye et al., 2022)	0.0718	0.9494	0.0844	0.9372	0.0898	0.9321	0.0962	0.9279
FEDformer	0.0889	0.9321	0.1006	0.9191	0.1154	0.9080	0.1202	0.9012
GP	0.1500	0.8670	0.1907	0.8334	0.1621	0.8394	0.1273	0.8818
GRU	0.1102	0.8597	0.1144	0.8623	0.1183	0.8472	-	-
GTS	0.0790	0.9291	0.0884	0.9187	0.0957	0.9135	0.0951	0.9098
GWN	0.0746	0.9459	0.0922	0.9310	0.0909	0.9267	0.0962	0.9226
HyDCNN	0.0832	0.9354	0.0898	0.9329	0.0921	0.9285	-	-
Informer	0.1337	0.8903	0.1532	0.8705	0.1635	0.8527	0.1834	0.8399
LSTNet	0.0864	0.9283	0.0931	0.9135	0.1007	0.9077	0.1007	0.9119
MAGL (Liu et al., 2022c)	0.0728	0.9476	0.0824	0.9377	0.0893	0.9299	0.0951	0.9240
MAGNN (Chen et al., 2023c)	0.0745	0.9476	0.0876	0.9323	0.0908	0.9282	0.0963	0.9217
MDST-GNN (He et al., 2022b)	0.0738	0.9454	0.0833	0.9346	0.0884	0.9264	0.0922	0.9222
MTGNN (Wu et al., 2020c)	0.0745	0.9474	0.0878	0.9316	0.0916	0.9278	0.0953	0.9234
MTGODE (Jin et al., 2023c)	0.0736	0.9430	0.0809	0.9340	0.0891	0.9279	-	-
MTHetGNN	0.0749	0.9456	0.0892	0.9307	0.0959	0.8783	0.0969	0.8782
MTNet	0.0840	0.9319	0.0901	0.9226	0.0934	0.9165	0.0969	0.9147
RNN-GRU	0.1102	0.8597	0.1144	0.8623	0.1183	0.8472	0.1295	0.8651
SARIMA	0.0906	0.9055	0.0999	0.8829	0.1026	0.8674	0.1036	0.8621
SCINet	0.0740	0.9494	0.0845	0.9387	0.0929	0.9305	0.0967	0.9270
SDGL (Li et al., 2023k)	0.0698	0.9534	0.0805	0.9445	0.0889	0.9351	0.0935	0.9301
SDLGNN	0.0726	0.9502	0.0820	0.9384	0.0896	0.9304	0.0947	0.9257
SDLGNN-Corr	0.0737	0.9475	0.0841	0.9346	0.0923	0.9263	0.0971	0.9227
StemGNN	0.0799	0.9490	0.0909	0.9397	0.0989	0.9342	0.1019	0.9209
TDG4-MSF (Miao et al., 2023)	0.0731	0.9499	0.0828	0.9371	0.0894	0.9306	0.0969	0.9246
Theta	0.0975	0.8906	0.1029	0.8723	0.1040	0.8576	0.1041	0.8595
TPGNN (Liu et al., 2022d)	0.0627	0.9417	0.0685	0.9362	0.0699	0.9285	0.0936	0.9293
TPA-LSTM	0.0823	0.9439	0.0916	0.9337	0.0964	0.9250	0.1006	0.9133
TRMF	0.1802	0.8538	0.2039	0.8424	0.2186	0.8304	0.3656	0.7471
VAR-MLP	0.1393	0.8708	0.1620	0.8389	0.1557	0.8192	0.1274	0.8679

et al., 2023). The TDG4-MSF model is composed of four components: temporal decomposition enhanced representation learning for extracting short and long term periodic patterns, graph structure learning, gated graph neural network depending on linear transformation for representation learning, and MLP-based output layer.

There are also other pairs of papers whose results can be compared. However, due to space limitations, we do not include tables comparing the results of just two papers in this "Generic" subsection. Instead, the reader is referred to Xu et al. (2024) and Yi et al. (2023) for the CSSE COVID-19 and ECG 5000 datasets; Chen et al. (2021) and Chen et al. (2022e) for the Bytom dataset; Zhang et al. (2023j) and Huang et al. (2023b) for the Jena weather dataset.

5.8. Other topics

This final subsection includes 34 papers that fall outside the previously discussed groups. The case studies include cellular traffic prediction, modulation classification, and other forecasting or classification problems. Given the heterogeneity of the papers, only a general overview is provided here, and no comparisons of the approaches or discussions of benchmarks are presented.

5.8.1. Overview

The interest in GNNs has grown so extensively that the selected themes are actually not sufficient to cover all relevant application domains. However, since only a few papers would belong to each potential additional theme, they are grouped under the label "Other topics". A frequently discussed topic in this "Other topics" category is cellular traffic prediction (Chen et al., 2023a; Gou & Zhang, 2023; Jiang et al., 2024a; Lin et al., 2021, 2024a; Wang et al., 2023j; Yu et al., 2021), in terms of SMS messages, calls, internet connections, phone's traffic statistics or locations, which are essential for the cellular network resource management system. Another topic included is modulation classification (Bai et al., 2023; Wang et al., 2023a; Xuan et al., 2022; Yin et al., 2024b; Zhang et al., 2024c), which is the process of determining the modulation used at the transmitter based on observations of the received signal (Hamkins & Simon, 2006). Four further areas of investigation to be added are the study of product demand and user preferences (Gandhi et al., 2021; Zhang et al., 2022c) to enable personalized experiences and recommendations, anomalous IoT intrusion detection (Altaf et al., 2024; Wang et al., 2024h), encrypted traffic classification (Diao et al., 2023b; Zhang et al., 2023a).

Other applications discussed in the papers of this subsection are urban spatio-temporal event prediction (Jin et al., 2022), prediction of the quality of operational processes (Zhang et al., 2023e), seismic intensity forecasting (Bloemheuvel et al., 2023b, with source code available at https://github.com/StefanBloemheuvel/GCNTimeseriesRegression), prediction of spatio-temporal dynamics with complex structures (Wen et al., 2023b), tailing dam monitoring (Ruan et al., 2023), subsurface production forecasting (Liu & Pyrcz, 2023), time series prediction for data centers maintenance (Shen et al., 2023), hydraulic runoff (Yang et al., 2023c), water demand forecasting (Zanfei et al., 2022), crime pre-

Table 37
Comparison of the average accuracy of the different models on the Exchange rate dataset for 3, 6, 12, and 24 steps time horizons, expressed in terms of RRSE and CORR. The numbers corresponding to the highest accuracy are underlined.

Time horizon	3 steps		6 steps		12 steps		24 steps	
Metrics	RRSE	CORR	RRSE	CORR	RRSE	CORR	RRSE	CORR
AGCRN	0.0269	0.9717	0.0331	0.9615	0.0374	0.9531	0.0476	0.9334
AGLG-GRU (Guo et al., 2023a)	0.0191	0.9792	0.0233	0.9701	0.0328	0.9548	0.0449	0.9372
AR	0.0228	0.9734	0.0279	0.9656	0.0353	0.9526	0.0445	0.9357
ARIMA	0.0198	0.9754	0.0261	0.9721	0.0344	0.9548	0.0445	0.9301
Autoformer	0.0291	0.9631	0.0379	0.9397	0.0441	0.9201	0.0501	0.9012
Crossformer	0.0226	0.9759	0.0269	0.9656	0.0358	0.9436	0.0489	0.9291
DPGNN (Li et al., 2024f)	0.0184	0.9797	0.0246	0.9715	0.0346	0.9564	0.0456	0.9386
DSTGN (Li et al., 2023j)	0.0179	0.9782	0.0250	0.9715	0.0346	0.9562	-	-
DSTIGNN (Gao et al., 2023c)	0.0173	0.9818	0.0244	0.9723	0.0333	0.9571	0.0430	0.9407
ESG (Ye et al., 2022)	0.0181	0.9792	0.0246	0.9717	0.0345	0.9564	0.0468	0.9392
FEDformer	0.0256	0.9701	0.0287	0.9555	0.0379	0.9385	0.0487	0.9190
GP	0.0239	0.8713	0.0272	0.8193	0.0394	0.8484	0.0580	0.8278
GRU	0.0192	0.9786	0.0264	0.9712	0.0408	0.9351	-	-
GTS	0.0180	0.9898	0.0260	0.9824	0.0333	0.9701	0.0442	0.9518
GWN	0.0251	0.9740	0.0300	0.9640	0.0381	0.9510	0.0486	0.9294
Informer	0.0882	0.9563	0.1081	0.9321	0.1301	0.8911	0.1521	0.8021
LSTNet	0.0226	0.9735	0.0280	0.9658	0.0356	0.9511	0.0449	0.9354
MAGL (Liu et al., 2022c)	0.0178	0.9797	0.0246	0.9716	0.0337	0.9567	0.0444	0.9361
MAGNN (Chen et al., 2023c)	0.0183	0.9778	0.0246	0.9712	0.0343	0.9557	0.0474	0.9339
MDST-GNN (He et al., 2022b)	0.0172	0.9811	0.0245	0.9727	0.0337	0.9578	0.0431	0.9392
MTGNN (Wu et al., 2020c)	0.0194	0.9786	0.0259	0.9708	0.0349	0.9551	0.0456	0.9372
MTHetGNN	0.0198	0.9769	0.0259	0.9701	0.0345	0.9539	0.0451	0.9360
MTNet	0.0212	0.9767	0.0258	0.9703	0.0347	0.9561	0.0442	0.9388
RNN-GRU	0.0192	0.9786	0.0264	0.9712	0.0408	0.9531	0.0626	0.9223
SARIMA	0.0197	0.9748	0.0253	0.9643	0.0338	0.9495	0.0444	0.9370
SCINet	0.0171	0.9787	0.0240	0.9704	0.0331	0.9553	0.0436	0.9396
SDGL (Li et al., 2023k)	0.0180	0.9808	0.0249	0.9730	0.0342	0.9583	0.0455	0.9402
StemGNN	0.0506	0.8871	0.0674	0.8703	0.0676	0.8499	0.0685	0.8738
TDG4-MSF (Miao et al., 2023)	0.0172	0.9825	0.0244	0.9718	0.0330	0.9569	0.0433	0.9386
Theta	0.0497	0.9738	0.0257	0.9656	0.0342	0.9510	0.0441	0.9323
TPA-LSTM	0.0174	0.9790	0.0241	0.9709	0.0341	0.9564	0.0444	0.9381
TPGNN (Liu et al., 2022d)	0.0174	0.9792	0.0250	0.9687	0.0350	0.9509	0.0458	0.9306
TRMF	0.0351	0.9142	0.0875	0.8123	0.0494	0.8993	0.0563	0.8678
VAR-MLP	0.0265	0.8609	0.0394	0.8725	0.0407	0.8280	0.0578	0.7675

diction (Zhou et al., 2024a, with source code available at https://github.com/ZJUDataIntelligence/HDM-GNN), polypropylene production data (Han et al., 2024c), tungsten flotation process (Wang et al., 2024j, with source code available at https://github.com/ywmcsu/SASGNN), talent and demand supply for labor market (Guo et al., 2022b, with source code available at https://github.com/gzn00417/DH-GEM), anomaly detection in microservice systems (Huang et al., 2023a, with source code available at https://github.com/ant-research/microservice_system_twin_graph_based_anomaly_detection[†]), and emergency supply forecasting for logistics systems (Lin et al., 2024b).

5.8.2. Datasets

Among the papers selected here, there are only four shared datasets, two for modulation classification, one for cellular traffic prediction, and one for botnet detection in IoT network traffic. However, the datasets are handled in different ways, either in terms of pre-processing techniques, selected time windows, or train/test split percentages. For this reason, the results of these papers are not directly comparable to each other.

The two datasets for modulation classification used in Wang et al. (2023a), Xuan et al. (2022), Bai et al. (2023) and Yin et al. (2024b) are RML2016.10a (https://www.kaggle.com/datasets/raindrops12/rml201610a, source paper: http://dx.doi.org/10.1007/978-3-319-44188-7_16) and RML2016.10b (https://www.kaggle.com/datasets/marwanabudeeb/rml201610b, source paper: https://pubs.gnuradio.org/index.php/grcon/article/view/11). They include 220,000 and 1.2 million samples respectively, in many modulation types. Each modulation type has 20 levels of signal-to-noise ratios at 2 dB intervals from -20 dB to 18 dB.

The cellular traffic prediction dataset used in Pan et al. (2021a), Wang et al. (2023j), Chen et al. (2023a), Jiang et al. (2024a), Gou and Zhang (2023) was proposed by Telecom Italia and MIT Media Lab during the "Telecom Italia Big Data Challenge", and it is available at https://dataverse.harvard.edu/dataverse/bigdatachallenge. The investigated geographical area is divided in a grid, and each cell records the number of SMS messages, calls, and wireless network traffic data in a 10 minutes interval.

Finally, the Bot-IoT dataset used in Altaf et al. (2024) and Wang et al. (2024h) and available at https://www.unsw.adfa.edu.au/unsw-canberra-cyber/cybersecurity/ADFA-NB15-Datasets/bot_iot.php, was created by designing a realistic network environment in the Cyber Range Lab of UNSW Canberra, and incorporates a combination of normal and botnet traffic.

6. Discussion

As stated in the Introduction, the aim of this SLR is to provide a comprehensive but also detailed overview of spatio-temporal GNN models for time series classification and forecasting used across different fields, assessing their performance and highlighting patterns that could guide future research. Existing literature was collected and synthesized to provide both an overview and a distillation of datasets, models, and tables of results, addressing the two sets of research questions posed in the Introduction.

Although our intention was to provide a broad and general perspective on widely used spatio-temporal GNN models and identify patterns that could be generalized across different domains and datasets, our analysis revealed that such generalizability is highly elusive. This characteristics stems from the primary strength of spatio-temporal GNNs: the possibility of explicitly modeling relationships between different variables, which is inherently dataset-dependent and highly heterogeneous across different applications. For instance, models for human mobility (e.g., traffic flow, epidemic spread) share intrinsic similarities but differ

Table 38
Comparison of the average accuracy of the different models on the Solar energy dataset for 3, 6, 12, and 24 steps time horizons, expressed in terms of RRSE and CORR. The numbers corresponding to the highest accuracy are underlined.

Time horizon	3 steps		6 steps		12 steps		24 steps	
Metrics	RRSE	CORR	RRSE	CORR	RRSE	CORR	RRSE	CORR
ADLGNN (Sriramulu et al., 2023)	0.1708	0.9866	0.2188	0.9768	0.2897	0.9551	0.4128	0.9060
AGCRN	0.1840	0.9841	0.2432	0.9708	0.3185	0.9487	0.4141	0.9087
AGLG-GRU (Guo et al., 2023a)	0.1762	0.9842	0.2302	0.9682	0.3021	0.9532	0.4130	0.9084
AR	0.2435	0.9710	0.3790	0.9263	0.5911	0.8107	0.8699	0.5314
ARIMA	0.2328	0.9739	0.3413	0.9402	0.4531	0.8886	0.5810	0.8133
Autoformer	0.1935	0.9784	0.2604	0.9651	0.3959	0.9111	0.6064	0.8180
Crossformer	0.1758	0.9801	0.2304	0.9679	0.3101	0.9437	0.4115	0.9001
DPGNN (Li et al., 2024f)	0.1794	0.9850	0.2364	0.9724	0.3003	0.9543	0.4091	0.9117
DSTGN (Li et al., 2023j)	0.1787	0.9867	0.2358	0.9721	0.3079	0.9513	-	-
DSTIGNN (Gao et al., 2023c)	0.1684	0.9869	0.2165	0.9773	0.2863	0.9584	0.4064	0.9118
ESG (Ye et al., 2022)	0.1708	0.9865	0.2278	0.9743	0.3073	0.9519	0.4101	0.9100
FEDformer	0.1901	0.9827	0.2444	0.9606	0.3502	0.9275	0.4851	0.8876
GP	0.2259	0.9751	0.3286	0.9448	0.5200	0.8518	0.7973	0.5971
GRU	0.1932	0.9823	0.2628	0.9675	0.4163	0.9150	-	-
GTS	0.1842	0.9842	0.2691	0.9645	0.3259	0.9481	0.4796	0.8678
GWN	0.1773	0.9846	0.2279	0.9743	0.3068	0.9527	0.4206	0.9055
HyDCNN	0.1806	0.9865	0.2335	0.9747	0.3094	0.9515	-	-
Informer	0.2134	0.9715	0.2701	0.9549	0.4331	0.8985	0.7017	0.7921
LSTNet	0.1843	0.9843	0.2559	0.9690	0.3254	0.9467	0.4643	0.887
MAGL (Liu et al., 2022c)	0.1678	0.9869	0.2220	0.9759	0.2998	0.9550	0.4188	0.9057
MAGNN (Chen et al., 2023c)	0.1771	0.9853	0.2361	0.9724	0.3015	0.9539	0.4108	0.9097
MDST-GNN (He et al., 2022b)	0.1764	0.9855	0.2321	0.9735	0.3082	0.9519	0.4119	0.9103
MTGNN (Wu et al., 2020c)	0.1778	0.9852	0.2348	0.9726	0.3109	0.9509	0.4270	0.9031
MTGODE (Jin et al., 2023c)	0.1693	0.9868	0.2171	0.9771	0.2901	0.9577	-	-
MTHetGNN	0.1838	0.9845	0.2600	0.9681	0.3169	0.9486	0.4231	0.9031
MTNet	0.1847	0.9840	0.2398	0.9723	0.3251	0.9462	0.4285	0.9013
RNN-GRU	0.1932	0.9823	0.2628	0.9675	0.4163	0.9150	0.4852	0.8823
SARIMA	0.2227	0.9760	0.3228	0.9461	0.4512	0.8900	0.5714	0.8184
SCINet	0.1775	0.9853	0.2301	0.9739	0.2997	0.9550	0.4081	0.9112
SDGL (Li et al., 2023k)	0.1699	0.9866	0.2222	0.9762	0.2924	0.9565	0.4047	0.9119
SDLGNN	0.1720	0.9864	0.2249	0.9757	0.3024	0.9547	0.4184	0.9051
SDLGNN-Corr	0.1806	0.9848	0.2378	0.9722	0.3042	0.9534	0.4173	0.9067
StemGNN	0.1839	0.9841	0.2612	0.9679	0.3564	0.9395	0.4768	0.8740
STG-NCDE	0.2346	0.9748	0.2908	0.9605	0.5149	0.8639	-	-
TDG4-MSF (Miao et al., 2023)	0.1746	0.9858	0.2348	0.9727	0.3082	0.9527	0.4031	0.9143
Theta	0.2442	0.9685	0.3327	0.9445	0.4488	0.8979	0.6092	0.8139
TPA-LSTM	0.1803	0.9850	0.2347	0.9742	0.3234	0.9487	0.4389	0.9081
TPGNN (Liu et al., 2022d)	0.1850	0.9840	0.2412	0.9716	0.3059	0.9529	0.3498	0.9710
VAR-MLP	0.1922	0.9829	0.2679	0.9655	0.4244	0.9058	0.6841	0.7149

in temporal scales, spatial resolution, and interaction types. Similarly, environmental applications such as weather forecasting and energy demand prediction are both influenced by climatic factors but rely on different variables and relationships.

We believe that a comprehensive perspective can be drawn after such an extensive examination of the available literature. Hence, we attempt now to discuss common patterns and insights that are not immediately apparent across different domains. In this section, we first address the research questions posed in the Introduction, then summarize prevailing research trends, and finally present a meta-analysis aimed at uncovering common insights.

6.1. Research questions

Most of the general overview questions (GQs) were addressed in the overview presented in Section 3. As for the tools, the GNN community mostly uses Python and PyTorch, although some researchers use TensorFlow. Unfortunately only few papers provide a link to the source code of the proposed model. Almost all papers are funded by public or private entities.

As for the specific questions (SQs), the answers are the following.

SQ1 (Applications). The three most investigated fields are "Mobility", "Environment", and "Generic". Regarding the first two thematic groups, their datasets can be naturally translated into graphs, which explains why they have been studied more extensively over time. In contrast, the "Generic" thematic group has only recently gained a significant interest. As for the differences among the thematic groups, the main ones are related to the definition of the graph, which is not always explicit, and the benchmarks used, often related to the mindset of specific communities. It is not easy to compare results across different applications and to determine the most promising fields. The studies in the "Generic" thematic group appear promising across a wide range of domains.

SQ2 (Graph construction). Most of the selected papers focus on pre-defined graph structures (when available), with the objective of extracting the maximum amount of information and enhancing the interpretability of the model. However, there is a recent growing interest in models that learn the graph structure and the edge weights themselves. While this trend toward adaptive graph learning is expected to gain momentum, the literature remains divided on whether learned or pre-defined adjacency matrices are preferable. The choice between these approaches should be based on the availability of domain knowledge and model performance requirements, requiring further research to establish clearer guidelines.

SQ3 (Taxonomy). As observed by Zeghina et al. (2024), there are two main approaches for the design of spatio-temporal GNNs: one that treats the spatial and temporal components in separate modules, and another that integrates and processes them together. The analysis of the collected papers reveals that the most common approach in literature is that of separate modules. Specifically, researchers very often address the spatial and temporal aspects of the problem independently from each other, and focus on each module separately. Hence,

Table 39
Comparison of the average accuracy of the different models on the Traffic dataset for 3, 6, 12, and 24 steps time horizons, expressed in terms of RRSE and CORR. The numbers corresponding to the highest accuracy are underlined.

Time horizon	3 steps		6 steps		12 steps		24 steps	
Metrics	RRSE	CORR	RRSE	CORR	RRSE	CORR	RRSE	CORR
ADLGNN (Sriramulu et al., 2023)	0.4047	0.9028	0.4201	0.8928	0.4299	0.8876	0.4416	0.8818
AGCRN	0.4379	0.8850	0.4635	0.8670	0.4694	0.8679	0.4707	0.8664
AGLG-GRU (Guo et al., 2023a)	0.4173	0.8958	0.4722	0.8541	0.4427	0.8755	0.4526	0.8842
AR	0.5991	0.7752	0.6218	0.7568	0.6252	0.7544	0.6300	0.7519
ARIMA	0.5841	0.7959	0.6194	0.7655	0.6197	0.7652	0.6248	0.7610
GP	0.6082	0.7831	0.6772	0.7406	0.6406	0.7671	0.5995	0.7909
GTS	0.4665	0.8695	0.4779	0.8582	0.4792	0.8589	0.4766	0.8573
GWN	0.4484	0.8801	0.4689	0.8674	0.4725	0.8646	0.4741	0.8646
HyDCNN	0.4198	0.8915	0.4290	0.8855	0.4352	0.8858	0.4423	0.8819
LSNet	0.4777	0.8721	0.4893	0.8690	0.4950	0.8614	0.4973	0.8588
MAGL (Liu et al., 2022c)	0.4058	0.9013	0.4189	0.8935	0.4308	0.8871	0.4417	0.8810
MAGNN (Chen et al., 2023c)	0.4097	0.8992	0.4555	0.8753	0.4423	0.8815	0.4434	0.8813
MDST-GNN (He et al., 2022b)	0.4162	0.8958	0.4461	0.8803	0.4377	0.8841	0.4452	0.8792
MTGNN (Wu et al., 2020c)	0.4162	0.8963	0.4754	0.8667	0.4461	0.8794	0.4535	0.8810
MTGODE (Jin et al., 2023c)	0.4127	0.9000	0.4259	0.8945	0.4329	0.8899	-	-
MTHetGNN	0.4826	0.8643	0.5198	0.8452	0.5147	0.8744	0.5250	0.8418
MTNet	0.4764	0.8728	0.4855	0.8681	0.4877	0.8644	0.5023	0.8570
RNN-GRU	0.5358	0.8511	0.5522	0.8405	0.5562	0.8345	0.5633	0.8300
SARIMA	0.5823	0.7967	0.5974	0.7837	0.6002	0.7811	0.6151	0.7697
SCINet	0.4216	0.8920	0.4414	0.8809	0.4495	0.8772	0.4453	0.8825
SDGL (Li et al., 2023k)	0.4142	0.9010	0.4475	0.8825	0.4584	0.8760	0.4571	0.8766
SDLGNN	0.4053	0.9017	0.4209	0.8925	0.4313	0.8868	0.4444	0.8801
SDLGNN-Corr	0.4227	0.8937	0.4378	0.8846	0.4576	0.8746	0.4579	0.8784
TDG4-MSF (Miao et al., 2023)	0.4029	0.9014	0.4196	0.8925	0.4294	0.8864	0.4366	0.8834
Theta	0.6071	0.7768	0.6241	0.7606	0.6271	0.7591	0.6012	0.7830
TPA-LSTM	0.4487	0.8812	0.4658	0.8717	0.4641	0.8717	0.4765	0.8629
TPGNN (Liu et al., 2022d)	0.3989	0.9232	0.4715	0.8945	0.4476	0.9028	0.4696	0.8858
TRMF	0.6708	0.6964	0.6261	0.7430	0.5956	0.7748	0.6442	0.7278
VAR-MLP	0.5582	0.8245	0.6570	0.7695	0.6023	0.7929	0.6146	0.7891

the proposed taxonomy of GNN models takes its main perspective from the point of view of the spatial component. The review indicates that convolutional approaches are the most prevalent, followed by attentional methods. Approximately 60 % of the models are purely convolutional, 22 % are purely attentional, and 10 % are hybrid convolutional-attentional. Additional statistics related to taxonomy distributions by year and research field are available in the GitHub repository associated with this review. With regard to the temporal component, the recurrent structures of GRUs and the attention mechanism are widely used.

SQ4 (Benchmark models). As for the benchmark models, there are many options available, and their choice depends on the specific application. In thematic groups such as “Energy”, “Finance”, “Health”, and “Predictive monitoring”, the focus tends to be on simpler statistical and non-GNN machine learning benchmarks, with only a limited use of GNN benchmarks. In the “Generic” group, many recent machine learning benchmark models based on the Transformer architecture have emerged. Notably, in “Mobility”, “Environment”, and “Generic” groups (which are also the most investigated fields), there are many reference GNN benchmark models. The most widely used GNN benchmarks, spanning all thematic groups, include: the graph convolutional neural network with long-short term memory (GC-LSTM) (Qi et al., 2019), spatio-temporal graph convolutional network (STGCN) (Yu et al., 2018), attention-based spatial-temporal graph convolutional network (ASTGCN) (Guo et al., 2019), diffusion convolutional recurrent neural network (DCRNN) (Li et al., 2018), and multivariate time series forecasting with graph neural network (MTGNN) (Wu et al., 2020c). These GNN benchmarks, mostly published between 2018 and 2020, represent some of the earliest and most cited works in spatio-temporal GNN literature. Almost all of them employ graph convolutional mechanisms, often Chebyshev-based or similar variants, reflecting the state-of-the-art at the time. In most cases, the adjacency matrix is pre-defined, often based on distances between measurement sites, whereas just one approach incorporates a learned adjacency matrix (i.e., MTGNN, which is one of the first models to use self-learned graph structures). In terms of application domains, four out of five of these benchmarks were originally developed to focus on “Mobility” or “Generic” tasks, with only GC-LSTM originally addressing environmental applications. Among these benchmarks, ASTGCN also explores attention mechanisms alongside graph convolutions and constitutes one of the earliest hybrid architectures. Overall, these benchmarks illustrate the early development of GNNs: graph convolution dominates, adjacency matrices are usually static, and mobility-related tasks are the most commonly studied.

SQ5 (Benchmark datasets). The datasets mentioned in the selected papers are closely related to the specific case of study. Even though some benchmark datasets are listed in the “Generic” thematic group, there is no common standard dataset for the entire spatio-temporal GNN research community. Hence, it would be beneficial for the community to agree on, and start adopting, some of the most commonly used datasets, with the goal of developing a shared benchmark dataset. Some possible common benchmark could be the ones presented in the “Mobility” and the “Generic” thematic group. Hopefully, this review could serve this purpose by providing comprehensive tables of the results of the models on different datasets to facilitate comparison between spatio-temporal GNN models.

SQ6 (Modeling paradigms). As for the modeling paradigm used in each paper, most of the selected papers work with a homogeneous graph, which models the relationships among multiple entities of the same nature. This is due to the fact that many basic GNN algorithms were originally developed for homogeneous graphs, and because it is easier to identify relationships between quantities of the same type. Also, in many cases, the focus is on multivariate series where the variables of interest and the target quantities are inherently of the same nature.

SQ7 (Metrics). Regarding the error metrics used in the papers, their choice is highly dependent on the specific case study. However, the most common ones are mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE) for forecasting problems, and accuracy for classification problems.

Table 40
Average number of datasets and benchmark models used, and percentage of papers with the link to the source code for each group.

Group	Datasets (avg.)	Benchmarks (avg.)	Code availability
Energy	1.6	5.7	3 %
Environment	1.3	6.6	23 %
Finance	1.5	6.3	7 %
Generic	4.5	10.6	56 %
Health	1.7	8.3	48 %
Mobility	2.8	9.4	35 %
Other	1.9	6.3	15 %
Predictive monitoring	2.2	7.9	22 %

6.2. Observed trends

Our analysis of papers from different domains indicates that some thematic groups have seen more intense research on GNN models than others. For instance, the papers in the "Mobility" and "Generic" groups generally present more complex models, likely reflecting the greater research effort in these fields, as evidenced by the larger number of published papers. In contrast, the "Finance" and "Health" thematic groups have fewer papers and often offer only a limited number of benchmarks for comparison. Another notable example is the "Energy" group, which has a relatively large number of papers, particularly in 2024. However, the related community tends to rely more on traditional econometrics or non-GNN machine learning approaches, and the GNN models proposed are generally less complex than those in other domains. Moreover, many papers in the "Energy" thematic group test their models on proprietary datasets, which further complicates model development across the group. Overall, this analysis suggests that some fields are more prone to the development of innovative and complex models, whereas others focus on adapting existing models to specific real-world problems. Consequently, we expect some form of cross-pollination between the communities, which is likely to reduce these differences over time. For readers interested in a more detailed view of how GNN taxonomies evolve across fields and over time, interactive charts are available in the GitHub repository accompanying this paper.

Another important aspect related to research trends is the focus on reproducibility and comparability of studies, which, more in general, is essential for advancing scientific knowledge. Some fields pay greater attention to reproducibility, facilitated by the availability of datasets, a larger number of benchmarks, and more detailed model descriptions. Table 40 shows the average number of datasets and benchmark models used, as well as the percentage of papers reporting the source code for each group.

6.3. Meta-analysis across groups

Here, we conduct a meta-analysis of the reviewed spatio-temporal GNNs models across multiple application domains. By definition, all models incorporate both spatial and temporal components, either arranged sequentially (space-then-time) or jointly (space-and-time). Beyond this common feature, designs vary widely, and our meta-analysis focuses on the key aspects that characterize these models, namely graph construction and spatial aggregation, aiming to reveal patterns where possible.

However, the highly fragmented research landscape makes identifying these trends challenging. We observed that many models are tailored to specific case studies, and differences in domain focus, limited reproducibility, and inconsistent experimental setups further complicate cross-domain comparisons and the extraction of generalizable insights. For this reason, rather than attempting a meta-analysis across the entire fragmented landscape of reviewed papers, we focused on the best-performing models within each domain to identify shared characteristics and emerging trends. In particular, we selected those models that, in the results tables, ranked among the top performers for the associated datasets and that were briefly discussed below each table. These models were gathered across all groups and are available in the GitHub repository associated with this work.

In this selected subset, models from the "Generic" and "Mobility" thematic groups are more numerous. This is not because they are inherently more important, but because these models offer greater comparability, having been evaluated across multiple common datasets in their original studies. For this reason, they are particularly suitable for this broader meta-analysis, which does not focus on highly specific use cases.

As for the determination of the graph structure, most models in the selected subset have a self-learning module. Pre-defined adjacency matrices based on physical distances, correlations, cosine similarities, or similar techniques remain more common in studies focused on specific tasks. From a historical perspective, early models relied more heavily on pre-defined adjacency matrices, whereas more recent works increasingly favor learned or hybrid adjacency matrices, often combining learned and pre-defined structures to enhance adaptivity and robustness. This shift toward learned or hybrid adjacency matrices, often implemented via self-learning modules, supports broader applicability across diverse domains. Among self-learning modules in spatio-temporal GNNs, two predominant approaches have emerged with comparable prevalence in the selected subset of papers: the method of the GWN model (Wu et al., 2019) and that of the MTGNN model (Wu et al., 2020c), both discussed in Subsection 4.4.

As for the spatial aggregation module, the subset reveals that graph convolution remains the dominant spatial aggregation mechanism in high-performing spatio-temporal GNNs, while attention-based spatial aggregation is less common. This suggests that the practical advantages of convolutional aggregation, in terms of efficiency and training stability, continue to make it preferable to attention mechanisms. The aggregation mechanism of recurrent GNNs, which defined the original GNN formulation, is instead almost entirely unused.

7. Limits, challenges, and future research directions

In this section the limitations and challenges of spatio-temporal GNN modeling will be discussed, together with directions for further research.

Comparability. As highlighted by Longa et al. (2023), the evaluation of GNN models has improved thanks to the introduction of the Open Graph Benchmark (OGB) (Hu et al., 2020), which provides a standardized evaluation framework and a variety of benchmark graph datasets. However, there is currently no standardized benchmark for spatio-temporal GNNs. As a result, each model is evaluated on its own selection of datasets, and this fragmentation makes it difficult to compare the results of different studies. To alleviate this problem, this review presented all the information gathered from the selected papers, including datasets, benchmarks, codes, and tables of results. All that is intended to serve as a detailed overview and a foundation for further exploration, in the hope that researchers will begin to examine the data collected in the presented tables and, over time, identify relevant datasets and benchmark models. Moreover, we encourage the authors to discuss the relationship between complexity and performance of the proposed models to facilitate a more comprehensive comparison.

Reproducibility. The limited availability of links to repositories, source code, and datasets makes it difficult to evaluate the progress of knowledge in spatio-temporal GNNs. Moreover, in many papers the authors do not give detailed information about the model and the graph structure, like definition of the graph, number of nodes, calculation of edge weights. This issue complicates the verification of results and the assessment of the reproducibility of experiments, which are essential to drive further research in this field. Without access to this fundamental information, it is extremely difficult to assess the accuracy and significance of the proposed models.

Poor information capacity. Another limitation of GNNs lies in the limited amount of information used in the design of the graph struc-

ture and the model definition. A poorly constructed graph with unrepresentative or overly sparse connections, as well as a lack of physical constraints in the equations of the model, can significantly affect the performance. Although efforts have been made to address these issues, such as integrating physical constraints through differential equations, these approaches are not always effective. Therefore, it is essential to develop new techniques to overcome these limitations.

Scalability. Spatio-temporal GNNs are widely used for modeling and analyzing large and complex time series-based network structures. However, GNN models often scale badly, and require a significant amount of memory and computing resources to calculate the adjacency matrix and node embeddings, especially in the case of dynamic graph structures. This challenge can result in high computational costs, and in many cases in the necessity of using intensively GPU devices. Therefore, the development of more scalable GNN models is crucial to facilitate time series analysis even in environments with limited computing power.

Heterogeneity. The majority of current GNN models are designed to deal with homogeneous graphs, where nodes and edges are all of the same nature. As a result, it would be challenging to use these GNNs with heterogeneous graphs which have different types of nodes and edges or different inputs. Therefore, further research is necessary to develop GNN models that can effectively capture the interactions between various types of nodes and edges.

Explainability. A crucial aspect for GNN models is explainability, intended as the ability to interpret and understand the decision-making processes implemented in them. Despite their attempt to explicitly model spatial relationships between series, GNNs are often considered as "black box" models. Remarkably, none of the selected papers adequately tackle the concept of explainability. Some models are claimed to be explainable because of the integration of non-linear physical laws (e.g., Sun et al., 2024a), while other papers claim explainability on the basis of the possibility to visualize a graph (e.g., Gong et al., 2024) or because they present a feature aggregation form that can be intuitively understood. In addition, other approaches focus on determining feature importance through tools such as Captum (Kokhlikyan et al., 2020), which enables the interpretation and understanding of PyTorch model predictions by exploring the features that contribute to a specific outcome (e.g., Ren et al., 2024). This highlights a research gap in this area. However, recent literature is beginning to investigate this important topic, as also discussed in Tang et al. (2023b). For instance, few papers studied perturbation-based explanation methods. Other approaches, such as GNNExplainer (Ying et al., 2019), aim to identify a small subset of node features that have a crucial role in GNN's predictions, as in Verdone et al. (2024) and Kim et al. (2024a). Recently, some researchers have started to explore graph counterfactuals as a means of generating explanations, as reviewed in Prado-Romero et al. (2024). For a recent survey on GNNs for explainable AI see Nandan et al. (2025).

Quasi-equilibrium learning. As pointed out in Subsection 4.2, GNNs were originally introduced by Scarselli et al. (2009) by promoting an extension of the backpropagation algorithm which exploits a fixed-point principle. The subsequent introduction of the notion of convolutional graph has fundamentally changed such computational scheme. It is worth mentioning that in contemporary GNNs there is no need to wait for the system to reach equilibrium. For example, the deep neural network scheme no longer requires weight-sharing. These improvements have led to successful applications in many real-world problems, where modern features contribute significantly to both accuracy and computational efficiency. However, when analyzing the processing of temporal information, GNNs are often implemented within a single graph domain where a temporal function is defined. This is a case where the original computational approach proposed by Scarselli et al. (2009) seems to be more adequate, especially when considering that the rate of weight updates is generally much slower than the rate of external temporal signals. This suggests the necessity of revisiting the process of convergence to the fixed point, and of exploring computational schemes which take place at quasi-equilibrium points. We expect that this approach can significantly alleviate the computational burden that is typical of the convergence to fixed-points required for spatio-temporal graph collections.

Broader directions. The field of time series modeling by means of GNNs is expected to expand in a set of further directions. While most of the reviewed studies focus on point forecasting with deterministic models, relatively few address probabilistic forecasting (e.g., Hu et al., 2024a; Wen et al., 2023a), which is crucial for assessing uncertainty in predictions. Another potential direction could be the integration of spatio-temporal GNNs with transformer-based architectures or large language models. Although studies are still limited, such models could help capture long term dependencies and complex patterns in time series data, yet not forgetting all possible limitations of LLMs in time series applications (Tan et al., 2024). Exploring these directions may help overcome current limitations in modeling uncertainty and complex temporal relationships, providing more informative and reliable results.

8. Conclusions

This paper presented the results of a SLR on the application of spatio-temporal GNN models to time series classification and forecasting problems in different fields. The interest on this subject comes from the fact that lately, GNNs have gained significant popularity due to their ability to process graph-structured data. This has led in more recent years to the development of spatio-temporal GNNs and their application to time series analysis, due to their ability to model dependencies between variables and across time points at once.

This SLR has brought forward two sets of research questions: generic questions which can be answered at the level of a bibliographic overview, and more specific questions regarding particular aspects of the proposed spatio-temporal GNN models. The answers to these questions provide a list of interesting considerations.

It has emerged that the majority of the models in the selected papers is characterized by a convolutional spatial aggregation. However, graph attentional models are also emerging as important tools. In addition, while the majority of the selected papers focus on models with a predefined graph structure, an increasing number of studies, particularly in the "Generic" thematic group, are beginning to develop models that learn the graph structure autonomously.

Another key point which results from the presented overview is that the current literature on spatio-temporal GNNs is very fragmented, as it was pictorially reported in Fig. 5. This can be attributed to the fact that the involved researchers come from different communities which focus on distinct application domains. As a result, there seems to be a lack of standardized datasets or benchmarks in the studies. The objective of this review was also to collect information on datasets, proposed models, links to source codes, benchmarks, and results, in order to provide common background information for future studies. To support this goal, the GitHub repository associated with this review offers interactive tools for sorting, filtering, and visualizing the results achieved by the different models, making it easier for researchers to explore and compare existing work.

A further major key point resulting from our review, which we believe should be emphasized in these conclusions, is the need for the spatio-temporal GNN research community to work on common datasets and develop comparable and reproducible models. That would enhance transparency, and it would make it easier for all researchers to reciprocally evaluate advancements in the field and to share them more easily.

CRediT authorship contribution statement

Flavio Corradini: Project administration, Funding acquisition, Supervision; **Flavio Gerosa:** Writing – review & editing, Visualization,

Investigation; **Marco Gori:** Writing – review & editing, Supervision; **Carlo Lucheroni:** Writing – review & editing, Supervision; **Marco Piangerelli:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization; **Martina Zannotti:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Author names appear in alphabetical order and do not reflect relative contributions.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Martina Zannotti reports financial support was provided by European Union. Marco Piangerelli reports financial support was provided by European Union. Carlo Lucheroni reports financial support was provided by European Union. Martina Zannotti reports financial support was provided by Syeew srl. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary material

Link to the GitHub repository containing information on the 366 reviewed papers organized by groups, along with interactive tables and charts: https://github.com/FlaGer99/SLR-Spatio-Temporal-GNN.git.

Appendix A. List of selected papers

Table A.41 lists all the papers included in this SLR, together with the year of publication, group they belong to, case study, and nature of the task (classification or forecasting).

Table A.41
List of the selected papers, with year, group they belong to, case study, and nature of the task.

Reference	Year	Group	Case study	Task
(Yu et al., 2020)	2020	Energy	Wind power	Forecasting
(Lin & Wu, 2021)	2021	Energy	Electric load	Forecasting
(He et al., 2022a)	2022	Energy	Wind power	Forecasting
(Simeunović et al., 2022a)	2022	Energy	Photovoltaic power	Forecasting
(Simeunović et al., 2022b)	2022	Energy	Photovoltaic power	Forecasting
(Zhao et al., 2022b)	2022	Energy	Power system transient dynamics	Forecasting
(Hu et al., 2022)	2022	Energy	Urban energy consumption	Forecasting
(Li, 2022)	2022	Energy	Wind power	Forecasting
(Wang et al., 2023k)	2023	Energy	Heat load	Forecasting
(Zhang et al., 2023d)	2023	Energy	Electricity load	Forecasting
(Wang et al., 2023h)	2023	Energy	Residential load	Forecasting
(Ganjouri et al., 2023)	2023	Energy	Electricity load	Forecasting
(Qin et al., 2023)	2023	Energy	Solar power	Forecasting
(Yang et al., 2024a)	2024	Energy	Wind power	Forecasting
(Yi et al., 2024)	2024	Energy	Wind power	Forecasting
(Zou et al., 2024b)	2024	Energy	Air conditioning control	Forecasting
(Hu et al., 2024c)	2024	Energy	Air conditioning control	Forecasting
(Rawal & Ahmad, 2024a)	2024	Energy	Electrical demand and prices	Forecasting
(Giamarelos & Zois, 2024)	2024	Energy	Electric load	Forecasting
(Zhang et al., 2024b)	2024	Energy	Electric load	Forecasting
(Liu et al., 2024b)	2024	Energy	Chiller energy consumption	Forecasting
(Miraki et al., 2024)	2024	Energy	Electricity demand	Forecasting
(Ida Evangeline et al., 2024)	2024	Energy	Electric power anomalies	Classification
(Rawal & Ahmad, 2024b)	2024	Energy	Electricity demand	Forecasting
(Huang et al., 2024b)	2024	Energy	Electricity consumption	Forecasting
(Boussaid et al., 2024)	2024	Energy	District heating networks	Forecasting
(Cai et al., 2024)	2024	Energy	Power quality disturbances	Classification
(Feng et al., 2024b)	2024	Energy	Residential load	Forecasting
(Verdone et al., 2024)	2024	Energy	Photovoltaic energy	Forecasting
(Zhang et al., 2023h)	2024	Energy	Electric vehicle charging stations	Forecasting
(Pu et al., 2024)	2024	Energy	Natural gas consumption	Forecasting
(Yu et al., 2024c)	2024	Energy	Networked microgrids	Forecasting
(Qiu et al., 2024)	2024	Energy	Multivariate time series	Forecasting
(Geng et al., 2021)	2021	Environment	Wind speed	Forecasting
(Sun et al., 2021)	2021	Environment	Sea temperature	Forecasting
(Chen et al., 2022b)	2022	Environment	Water temperature, stream flow	Forecasting
(Pei et al., 2022)	2022	Environment	PM 2.5 concentration	Forecasting
(Lira et al., 2022)	2022	Environment	Frost	Both
(Wang et al., 2022b)	2022	Environment	Sea temperature	Forecasting
(Azmat et al., 2023)	2023	Environment	Soil Moisture	Forecasting
(Chen et al., 2023d)	2023	Environment	Air quality index	Forecasting
(Liu & Li, 2023)	2023	Environment	PM 2.5 concentration	Forecasting
(Su et al., 2023)	2023	Environment	PM 2.5 concentration	Forecasting
(Li et al., 2023f)	2023	Environment	PM 2.5 concentration	Forecasting
(Ding & Noh, 2023)	2023	Environment	Air quality index	Forecasting
(Ni et al., 2023)	2023	Environment	PM 2.5 concentration	Forecasting
(Kim et al., 2023a)	2023	Environment	PM 2.5 concentration	Forecasting
(Yang et al., 2023a)	2023	Environment	Sea temperature	Forecasting

Table A.41
Continued

(Bentsen et al., 2023a)	2023	Environment	Wind speed	Forecasting
(Li et al., 2023a)	2023	Environment	Water quality	Forecasting
(Ren et al., 2023)	2023	Environment	Wind speed	Forecasting
(Zhang et al., 2023i)	2023	Environment	Significant wave height	Forecasting
(Kim et al., 2023b)	2023	Environment	Sea temperature	Forecasting
(Bentsen et al., 2023b)	2023	Environment	Wind speed	Forecasting
(Pan et al., 2023)	2023	Environment	Sea temperature	Forecasting
(Gao et al., 2023b)	2023	Environment	Sea temperature	Forecasting
(Bai & Tahmasebi, 2022)	2023	Environment	Groundwater level	Forecasting
(Gao et al., 2023a)	2023	Environment	Wind speed	Forecasting
(Peng et al., 2023)	2023	Environment	Rainfall	Forecasting
(Dong et al., 2023)	2023	Environment	Wind speed	Forecasting
(Sheng et al., 2023)	2023	Environment	Sea temperature	Forecasting
(He et al., 2024a)	2024	Environment	Weather	Forecasting
(Liao et al., 2024a)	2024	Environment	PM2.5 prediction	Forecasting
(Li et al., 2024d)	2024	Environment	Sea clutter	Forecasting
(Kim et al., 2024a)	2024	Environment	Plankton dynamics	Forecasting
(Taccari et al., 2024)	2024	Environment	Groundwater data	Forecasting
(Gong et al., 2024)	2024	Environment	Carbon emission	Forecasting
(Ren et al., 2024)	2024	Environment	PM2.5 prediction	Forecasting
(Wu & Kang, 2024)	2024	Environment	Water demand	Forecasting
(Wu et al., 2024a)	2024	Environment	Water quality and flow rate	Forecasting
(Seol et al., 2024)	2024	Environment	Weather	Forecasting
(Liu et al., 2024c)	2024	Environment	Wind speed scenario	Forecasting
(Chen et al., 2024c)	2024	Environment	Air quality	Forecasting
(Wang et al., 2024l)	2024	Environment	Temperature	Forecasting
(Xia et al., 2024)	2024	Environment	Air quality	Forecasting
(Bobakov et al., 2024)	2024	Environment	Greenhouse gas concentrations	Forecasting
(Sharma et al., 2022)	2022	Finance	Energy markets	Forecasting
(Xiang et al., 2022)	2022	Finance	Stock prices	Classification
(Huang et al., 2022)	2022	Finance	Stock prediction	Classification
(Li & Yao, 2022)	2022	Finance	Investment prediction	Forecasting
(Cheng et al., 2022)	2022	Finance	Financial prediction	Classification
(Pang et al., 2023)	2023	Finance	Stock prediction	Classification
(Tian et al., 2023)	2023	Finance	Stock prediction	Classification
(Wang et al., 2023f)	2023	Finance	Stock prediction	Classification
(Sun et al., 2023)	2023	Finance	Stock prediction	Classification
(Huang et al., 2023c)	2023	Finance	Trading	Classification
(Yang et al., 2023d)	2023	Finance	Sale prediction	Forecasting
(Niu et al., 2024)	2024	Finance	Supply chain demand	Forecasting
(Lei & Song, 2024)	2024	Finance	Stock market volatility	Forecasting
(Chen et al., 2024b)	2024	Finance	Stock trend	Classification
(Deng et al., 2020)	2020	Health	Epidemics	Forecasting
(Segovia Dominguez et al., 2021)	2021	Health	Covid 19 severity	Forecasting
(Zheng et al., 2021)	2021	Health	Epidemics	Forecasting
(Murphy et al., 2021)	2021	Health	Epidemic prediction	Forecasting
(Chen et al., 2022a)	2022	Health	Epilepsy diagnosis	Classification
(Hy et al., 2022)	2022	Health	Epidemics	Forecasting
(Ma et al., 2022)	2022	Health	Epidemics	Forecasting
(Li et al., 2022e)	2022	Health	Epidemic prediction	Forecasting
(Oliveira et al., 2022)	2022	Health	Epidemic prediction	Forecasting
(Cai et al., 2023)	2023	Health	Epilepsy diagnosis	Classification
(Wang et al., 2023d)	2023	Health	Sleep stage, emotion recognition	Classification
(Wang et al., 2023c)	2023	Health	Epilepsy diagnosis	Classification
(Zhang et al., 2023c)	2023	Health	Epidemic prediction	Forecasting
(Yu et al., 2023)	2023	Health	Epidemic prediction	Forecasting
(Zhang et al., 2023g)	2023	Health	Disease diagnosis	Classification
(Xu et al., 2022)	2023	Health	Clinical risk classification	Classification
(Liu et al., 2024d)	2024	Health	Infectious disease	Forecasting
(Zhu et al., 2024a)	2024	Health	EEG emotion recognition	Classification
(Guo & Wang, 2024)	2024	Health	EEG emotion recognition	Classification
(Yanqin et al., 2024)	2024	Health	Epidemic	Forecasting
(Zhu et al., 2024b)	2024	Health	Epidemic	Forecasting
(Mao et al., 2024)	2024	Health	Epidemic	Forecasting
(Kim et al., 2024b)	2024	Health	Epidemic	Forecasting
(He & Shin, 2020a)	2020	Mobility	E-Scooter distribution	Forecasting
(He & Shin, 2020b)	2020	Mobility	Bike sharing	Forecasting
(Wang et al., 2020)	2020	Mobility	Urban traffic	Forecasting
(Bai et al., 2020)	2020	Mobility	Urban traffic	Forecasting
(Chen et al., 2020a)	2020	Mobility	Urban traffic	Forecasting
(Zhang et al., 2020c)	2020	Mobility	Urban traffic	Forecasting
(Lu et al., 2020)	2020	Mobility	Urban traffic	Forecasting
(Park et al., 2020)	2020	Mobility	Urban traffic	Forecasting
(Ou et al., 2020)	2020	Mobility	Metro flow	Forecasting
(Xie et al., 2020b)	2020	Mobility	Urban traffic	Forecasting
(Chen et al., 2020b)	2020	Mobility	Urban traffic	Forecasting

Table A.41
Continued

(Han et al., 2021)	2021	Mobility	Urban traffic	Forecasting
(Fang et al., 2021)	2021	Mobility	Urban traffic	Forecasting
(Li et al., 2021d)	2021	Mobility	Urban traffic	Forecasting
(Li et al., 2021c)	2021	Mobility	Urban traffic	Forecasting
(Xia et al., 2021b)	2021	Mobility	Crowd flow	Forecasting
(Wang et al., 2021)	2021	Mobility	Passenger demand	Forecasting
(Shao et al., 2022b)	2022	Mobility	Urban traffic	Forecasting
(Lu et al., 2022b)	2022	Mobility	Urban traffic	Forecasting
(Shao et al., 2022c)	2022	Mobility	Urban traffic	Forecasting
(Lan et al., 2022)	2022	Mobility	Urban traffic	Forecasting
(Liu et al., 2022a)	2022	Mobility	Urban traffic	Forecasting
(Feng & Tassiulas, 2022)	2022	Mobility	Urban traffic	Forecasting
(Li et al., 2022b)	2022	Mobility	Urban traffic	Forecasting
(Tang et al., 2022)	2022	Mobility	Urban traffic	Forecasting
(Ramhormozi et al., 2022)	2022	Mobility	Urban traffic	Forecasting
(Lu et al., 2022a)	2022	Mobility	Urban traffic	Forecasting
(Li et al., 2022a)	2022	Mobility	Crowd flow	Forecasting
(Li et al., 2022c)	2022	Mobility	Urban traffic	Forecasting
(Zhang et al., 2022a)	2022	Mobility	Connected internet of vehicles	Forecasting
(Liao et al., 2022)	2022	Mobility	Taxi demand	Forecasting
(Zhang & Guo, 2022)	2022	Mobility	Urban traffic	Forecasting
(Zhao et al., 2022a)	2022	Mobility	Metro passengers	Forecasting
(Khaled et al., 2022)	2022	Mobility	Urban traffic	Forecasting
(Lu et al., 2022c)	2022	Mobility	Urban traffic	Forecasting
(Bui et al., 2022)	2022	Mobility	Urban traffic	Forecasting
(Cai et al., 2022)	2022	Mobility	Flight delay	Forecasting
(Gu & Deng, 2022)	2022	Mobility	Urban traffic	Forecasting
(Cao et al., 2022)	2022	Mobility	Urban traffic	Forecasting
(Ding et al., 2022)	2022	Mobility	Bicycle demand	Forecasting
(Jiang et al., 2022)	2022	Mobility	Urban traffic	Forecasting
(Jin et al., 2023d)	2023	Mobility	Urban traffic	Forecasting
(Fang et al., 2023a)	2023	Mobility	Urban traffic	Forecasting
(Zhu et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Gupta et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Fan et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Wu et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Wang et al., 2023e)	2023	Mobility	Urban traffic congestion	Forecasting
(Hajisafi et al., 2023)	2023	Mobility	Visitation patterns	Forecasting
(Li et al., 2023c)	2023	Mobility	Urban traffic congestion	Classification
(Ma et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Hu et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Wölker et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Dai et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Li et al., 2023e)	2023	Mobility	Urban traffic	Forecasting
(Li et al., 2023b)	2023	Mobility	Urban traffic	Forecasting
(Liu et al., 2023c)	2023	Mobility	Urban traffic	Forecasting
(Liu et al., 2023b)	2023	Mobility	Urban traffic	Forecasting
(Jin et al., 2023a)	2023	Mobility	Urban traffic	Forecasting
(Li et al., 2023d)	2023	Mobility	Urban traffic	Forecasting
(Lablack & Shen, 2023)	2023	Mobility	Urban traffic	Forecasting
(Kumar et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Liang et al., 2023)	2023	Mobility	Bike sharing demand	Forecasting
(Yang et al., 2023b)	2023	Mobility	Urban traffic	Forecasting
(Guo et al., 2023b)	2023	Mobility	Urban traffic	Forecasting
(Gu et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Zhao et al., 2023)	2023	Mobility	Urban traffic	Forecasting
(Diao et al., 2023a)	2023	Mobility	Urban traffic	Forecasting
(Jiang et al., 2024b)	2024	Mobility	Urban traffic	Forecasting
(Zhang et al., 2024f)	2024	Mobility	Urban traffic	Forecasting
(Hu et al., 2024b)	2024	Mobility	Urban traffic	Forecasting
(Gao et al., 2024a)	2024	Mobility	Urban traffic	Forecasting
(Zou et al., 2024a)	2024	Mobility	Urban traffic	Forecasting
(Dan et al., 2024)	2024	Mobility	Urban traffic	Forecasting
(Zhou et al., 2024b)	2024	Mobility	Urban traffic	Forecasting
(Yu et al., 2024b)	2024	Mobility	Urban traffic	Forecasting
(Li et al., 2024c)	2024	Mobility	Urban traffic	Forecasting
(Chen et al., 2025)	2024	Mobility	Urban traffic	Forecasting
(Jakhmola et al., 2024)	2024	Mobility	Urban traffic	Forecasting
(Huo et al., 2024)	2024	Mobility	Urban traffic	Forecasting
(Wang et al., 2024d)	2024	Mobility	Metro flow traffic	Forecasting
(Zang et al., 2024)	2024	Mobility	Urban traffic	Forecasting
(Wei et al., 2024b)	2024	Mobility	Urban traffic	Forecasting
(Peng et al., 2024)	2024	Mobility	Network traffic volume	Forecasting
(Bikram et al., 2024)	2024	Mobility	Traffic speed	Forecasting
(Kwak et al., 2024)	2024	Mobility	Traffic speed	Forecasting
(Sánchez-Rada et al., 2024)	2024	Mobility	Urban traffic	Forecasting
(Singh et al., 2024)	2024	Mobility	Urban traffic	Forecasting

Table A.41
Continued

(Li et al., 2024g)	2024	Mobility	Urban traffic	Forecasting
(Wu et al., 2024c)	2024	Mobility	Airport performances	Forecasting
(Zhao et al., 2024)	2024	Mobility	Urban traffic	Forecasting
(Wei et al., 2024a)	2024	Mobility	Urban traffic	Forecasting
(Shin & Yoon, 2024)	2024	Mobility	Urban traffic	Forecasting
(Wang et al., 2024a)	2024	Mobility	Urban traffic	Forecasting
(Wu et al., 2024b)	2024	Mobility	Flight delay prediction	Forecasting
(Li et al., 2024a)	2024	Mobility	Traffic speed	Forecasting
(Liao et al., 2024c)	2024	Mobility	Urban traffic	Forecasting
(Feng et al., 2024c)	2024	Mobility	Bike sharing demand	Forecasting
(Han et al., 2024b)	2024	Mobility	Urban traffic	Forecasting
(Wang et al., 2024e)	2024	Mobility	Urban traffic	Forecasting
(Fang et al., 2024)	2024	Mobility	Urban traffic	Forecasting
(Kong et al., 2024a)	2024	Mobility	Bus stop mobility pattern	Forecasting
(Li et al., 2021a)	2021	Predictive monitoring	Fault diagnosis	Classification
(Mylonas & Chatzi, 2021)	2021	Predictive monitoring	Remaining useful life	Forecasting
(Han & Woo, 2022)	2022	Predictive monitoring	Anomaly detections	Forecasting
(Li et al., 2022d)	2022	Predictive monitoring	Anomaly detection	Classification
(Yang et al., 2022)	2022	Predictive monitoring	Remaining useful life)	Forecasting
(Kong et al., 2022)	2022	Predictive monitoring	Remaining useful life	Forecasting
(Lee et al., 2023)	2023	Predictive monitoring	Anomaly detection	Classification
(Hojjati et al., 2023)	2023	Predictive monitoring	Anomaly detection	Classification
(Li et al., 2023g)	2023	Predictive monitoring	Anomaly detection	Forecasting
(Van Gompel et al., 2023)	2023	Predictive monitoring	Fault diagnosis	Classification
(Yuan et al., 2023)	2023	Predictive monitoring	Fault diagnosis	Classification
(Ning et al., 2023)	2023	Predictive monitoring	Fault diagnosis	Classification
(Zhang et al., 2023f)	2023	Predictive monitoring	Fault prediction	Forecasting
(Wang et al., 2023i)	2023	Predictive monitoring	Remaining useful life	Forecasting
(Chen & Zeng, 2023)	2023	Predictive monitoring	Remaining useful life	Forecasting
(Wang et al., 2023b)	2023	Predictive monitoring	Remaining useful life	Forecasting
(Wei & Wu, 2023)	2023	Predictive monitoring	Remaining useful life	Forecasting
(Lei et al., 2023)	2023	Predictive monitoring	Fault diagnosis	Classification
(Fan et al., 2024)	2024	Predictive monitoring	Photovoltaic degradation	Forecasting
(Liu et al., 2024e)	2024	Predictive monitoring	Anomaly detection	Classification
(Malarkkan et al., 2024)	2024	Predictive monitoring	Anomaly detection	Classification
(Li et al., 2024e)	2024	Predictive monitoring	Anomaly detection	Classification
(Chen et al., 2024a)	2024	Predictive monitoring	Motor temperature	Forecasting
(Kovalenko et al., 2024)	2024	Predictive monitoring	Fault diagnosis and detection	Classification
(Feng et al., 2024a)	2024	Predictive monitoring	Root cause localization	Forecasting
(Wang et al., 2024f)	2024	Predictive monitoring	Fault diagnosis	Classification
(Gao et al., 2024b)	2024	Predictive monitoring	Outlier detection	Classification
(Zheng et al., 2024b)	2024	Predictive monitoring	Anomaly detection	Classification
(Zhang et al., 2024d)	2024	Predictive monitoring	Remaining useful life	Forecasting
(Liao et al., 2024b)	2024	Predictive monitoring	Anomaly detection	Classification
(Li et al., 2024b)	2024	Predictive monitoring	Sensor data	Forecasting
(Guo et al., 2024)	2024	Predictive monitoring	Anomaly detection	Classification
(Sun et al., 2024b)	2024	Predictive monitoring	Process factors	Forecasting
(Buchhorn et al., 2023)	2024	Predictive monitoring	Anomaly detection	Classification
(Zheng et al., 2024a)	2024	Predictive monitoring	Anomaly detection	Classification
(Wang et al., 2024b)	2024	Predictive monitoring	Fault diagnosis	Classification
(Zhang et al., 2024a)	2024	Predictive monitoring	Fault diagnosis	Classification
(Kong et al., 2024b)	2024	Predictive monitoring	Remaining useful life	Forecasting
(He et al., 2024b)	2024	Predictive monitoring	Anomaly detection	Classification
(Wang et al., 2024c)	2024	Predictive monitoring	Fault diagnosis	Classification
(Lin et al., 2021)	2021	Other	Cellular traffic	Forecasting
(Gandhi et al., 2021)	2021	Other	Product demand	Forecasting
(Pan et al., 2021a)	2021	Other	Cellular traffic	Forecasting
(Yu et al., 2021)	2021	Other	Cellular Network Traffic	Forecasting
(Guo et al., 2022b)	2022	Other	Talent demand and supply	Forecasting
(Xuan et al., 2022)	2022	Other	Modulation classification	Classification
(Jin et al., 2022)	2022	Other	Spatial temporal event prediction	Forecasting
(Zhang et al., 2022c)	2022	Other	App popularity	Forecasting
(Zanfei et al., 2022)	2022	Other	Water demand	Forecasting
(Zhang et al., 2023a)	2023	Other	Encrypted traffic	Classification
(Gou & Zhang, 2023)	2023	Other	Cellular traffic	Forecasting
(Wang et al., 2023a)	2023	Other	Modulation classification	Classification
(Diao et al., 2023b)	2023	Other	Encrypted traffic classification	Classification
(Zhang et al., 2023e)	2023	Other	Quality indicators prediction	Forecasting
(Wang et al., 2023j)	2023	Other	Cellular traffic prediction	Forecasting
(Bloemheuvel et al., 2023b)	2023	Other	Seismic data	Forecasting
(Wen et al., 2023b)	2023	Other	Structural dynamics	Forecasting
(Ruan et al., 2023)	2023	Other	Tailing dam monitoring	Forecasting
(Liu & Pyrcz, 2023)	2023	Other	Subsurface production	Forecasting
(Chen et al., 2023a)	2023	Other	Cellular Network Traffic	Forecasting
(Shen et al., 2023)	2023	Other	Data centers maintenance	Forecasting

Table A.41
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(Yang et al., 2023c)	2023	Other	Hydraulic runoff	Forecasting
(Bai et al., 2023)	2023	Other	Modulation classification	Classification
(Huang et al., 2023a)	2024	Other	Anomaly in microservice system	Classification
(Lin et al., 2024b)	2024	Other	Emergency supply	Forecasting
(Han et al., 2024c)	2024	Other	Polypropylene production	Forecasting
(Altaf et al., 2024)	2024	Other	Botnet detection	Classification
(Lin et al., 2024a)	2024	Other	Cellular KPI prediction	Forecasting
(Wang et al., 2024j)	2024	Other	Tungsten floatation plant	Forecasting
(Zhang et al., 2024c)	2024	Other	Modulation recognition	Classification
(Wang et al., 2024h)	2024	Other	IoT intrusion detection	Classification
(Yin et al., 2024b)	2024	Other	Modulation recognition	Classification
(Zhou et al., 2024a)	2024	Other	Crime prediction	Forecasting
(Jiang et al., 2024a)	2024	Other	Mobile traffic prediction	Forecasting
(Yi & Park, 2020)	2020	Generic	Multivariate time series	Forecasting
(Lu & Li, 2020)	2020	Generic	Multivariate time series	Forecasting
(Wu et al., 2020c)	2020	Generic	Multivariate time series	Forecasting
(Cao et al., 2020)	2020	Generic	Multivariate time series	Forecasting
(Shang et al., 2021)	2021	Generic	Multivariate time series	Forecasting
(Cui et al., 2021)	2021	Generic	Multivariate time series	Forecasting
(Chen et al., 2021)	2021	Generic	Multivariate time series	Forecasting
(Su et al., 2021)	2021	Generic	Multivariate time series	Forecasting
(Rozemberczki et al., 2021)	2021	Generic	Multivariate time series	Forecasting
(Mondal et al., 2021)	2021	Generic	Multivariate time series	Classification
(Huang et al., 2021b)	2021	Generic	Generic	Both
(Zhang et al., 2022b)	2022	Generic	Multivariate time series	Forecasting
(Ye et al., 2022)	2022	Generic	Multivariate time series	Forecasting
(Chen et al., 2022e)	2022	Generic	Time series	Forecasting
(Liu et al., 2022d)	2022	Generic	Multivariate time series	Forecasting
(Chen et al., 2022d)	2022	Generic	Multivariate time series	Forecasting
(Liu et al., 2022c)	2022	Generic	Multivariate time series	Forecasting
(Zha et al., 2022)	2022	Generic	Multivariate time series	Classification
(Chen et al., 2022c)	2022	Generic	Multivariate time series	Forecasting
(Chen & Xie, 2022)	2022	Generic	Multivariate time series	Forecasting
(Wang et al., 2022c)	2022	Generic	Multivariate time series	Forecasting
(He et al., 2022b)	2022	Generic	Multivariate time series	Forecasting
(Fang et al., 2023b)	2023	Generic	Multivariate time series	Both
(Huang et al., 2023b)	2023	Generic	Multivariate time series	Forecasting
(Yi et al., 2023)	2023	Generic	Multivariate time series	Forecasting
(Cini et al., 2023a)	2023	Generic	Multivariate time series	Forecasting
(Wen et al., 2023a)	2023	Generic	Multivariate time series	Forecasting
(Tang et al., 2023b)	2023	Generic	Multivariate time series	Forecasting
(Chen et al., 2023e)	2023	Generic	Multivariate time series	Forecasting
(Tang et al., 2023a)	2023	Generic	Multivariate time series	Forecasting
(Oskarsson et al., 2023)	2023	Generic	Multivariate time series	Forecasting
(Chen et al., 2023b)	2023	Generic	Batch workloads	Forecasting
(Li et al., 2023h)	2023	Generic	Node classification for websites	Classification
(Han et al., 2023)	2023	Generic	Clinical risk classification	Classification
(Cini et al., 2023b)	2023	Generic	Sensor network	Forecasting
(Li et al., 2023j)	2023	Generic	Multivariate time series	Forecasting
(Gao et al., 2023c)	2023	Generic	Multivariate time series	Forecasting
(Jin et al., 2023c)	2023	Generic	Multivariate time series	Forecasting
(Zhang et al., 2023j)	2023	Generic	Long term series forecasting	Forecasting
(Duan et al., 2023)	2023	Generic	Multivariate time series	Forecasting
(Li et al., 2023k)	2023	Generic	Multivariate time series	Forecasting
(Guo et al., 2023a)	2023	Generic	Multivariate time series	Forecasting
(Chen et al., 2023c)	2023	Generic	Multivariate time series	Forecasting
(Miao et al., 2023)	2023	Generic	Multivariate time series	Forecasting
(Wang et al., 2023g)	2023	Generic	Multivariate time series	Forecasting
(Sriramulu et al., 2023)	2023	Generic	Multivariate time series	Forecasting
(Kim et al., 2023c)	2023	Generic	Multivariate time series	Forecasting
(Zhan et al., 2023)	2023	Generic	Multivariate time series	Forecasting
(Chung et al., 2023)	2023	Generic	Multivariate time series	Forecasting
(Bloemheuvel et al., 2023a)	2023	Generic	Impact of graph construction	Forecasting
(Xu et al., 2024)	2024	Generic	Multivariate time series	Forecasting
(Yu et al., 2024a)	2024	Generic	Multivariate time series	Forecasting
(Yalavarthi et al., 2024)	2024	Generic	Multivariate time series	Forecasting
(Marisca et al., 2024)	2024	Generic	Multivariate time series	Forecasting
(Zhang et al., 2024e)	2024	Generic	Multivariate time series	Forecasting
(Ma et al., 2024)	2024	Generic	Multivariate time series	Forecasting
(Younis & Ahmadi, 2024)	2024	Generic	Multivariate time series	Classification
(Hu et al., 2024a)	2024	Generic	Multivariate time series	Forecasting
(Zhang et al., 2023k)	2024	Generic	Multivariate time series	Forecasting
(Liang et al., 2024a)	2024	Generic	Multivariate time series	Forecasting
(Du et al., 2024)	2024	Generic	Multivariate time series	Classification
(Gui et al., 2024)	2024	Generic	Multivariate time series	Classification
(Wang et al., 2024i)	2024	Generic	Multivariate time series	Both

Table A.41
Continued

(Han et al., 2024a)	2024	Generic	Multivariate time series	Forecasting
(Liu et al., 2024a)	2024	Generic	Multivariate time series	Classification
(Li & Tang, 2024)	2024	Generic	Multivariate time series	Forecasting
(Ge et al., 2024)	2024	Generic	Multivariate time series	Classification
(He et al., 2024c)	2024	Generic	Multivariate time series	Forecasting
(Huang et al., 2024a)	2024	Generic	Multivariate time series	Forecasting
(Yin et al., 2024a)	2024	Generic	Multivariate time series	Forecasting
(Wang et al., 2024g)	2024	Generic	Multivariate time series	Forecasting
(Sun et al., 2024a)	2024	Generic	Multivariate time series	Forecasting
(Wang et al., 2024k)	2024	Generic	Multivariate time series	Both
(Shaik et al., 2024)	2024	Generic	Multivariate time series	Forecasting
(Li et al., 2024f)	2024	Generic	Multivariate time series	Forecasting
(Hong et al., 2025)	2024	Generic	Multivariate time series	Classification
(Yang et al., 2024b)	2024	Generic	Multivariate time series	Forecasting

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