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A Comprehensive Study on the Prediction of Concrete Compressive Strength

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A Comprehensive Study on the Prediction of Concrete Compressive Strength

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Abstract: There is an extensive body of research in the literature focusing on predicting the mechanical properties of concrete, such as compressive strength. Summarizing the current studies following the valuable contributions of researchers will serve as a guide for future studies and researchers. To this end, this study aims to identify the key authors, sources, institutions, and countries that have contributed to the prediction of concrete compressive strength. Additionally, it aims to provide researchers with comprehensive information on prominent research themes, trends, and gaps in the literature related to the prediction of concrete compressive strength. For this purpose, 2319 articles on the prediction of concrete compressive strength published from 2000 to 19th August 2024 were identified through the Scopus Database. The scientific measurement analyses were conducted using VOSviewer software. Upon reviewing the relevant research, it was found that machine learning methods are frequently used in predicting concrete compressive strength. In this context, the study will make significant contributions to the literature by examining leading institutions, countries, authors, and sources in the field, synthesizing data, and highlighting research areas, gaps, and trends related to concrete compressive strength prediction.

Keywords: concrete; compressive strength; machine learning; mechanical properties; scientometric analysis

1. Introduction

With the increase in population, the rising demand for concrete has led to its widespread use in the construction of underground, surface, and water facilities [1]. Furthermore, parameters such as strength, durability, safety, service life, and cost-effectiveness contribute to concrete's popularity as a building material [2–5] The widespread use of concrete especially necessitates the accurate determination of its compressive strength. Today, the compressive strength of concrete can be determined through destructive testing methods and predicted using non-destructive testing methods. The reliable method of destructive testing is generally performed in a laboratory setting. However, these tests are time-consuming, costly, and impractical [6]. or this reason, research focusing on the practical and reliable identification, prediction, and improvement of concrete compressive strength has become an important area of study. As seen in the literature, there is a growing interest in predicting the compressive strength of concrete without performing mechanical experiments.

In recent years, advances in artificial intelligence have contributed to the development of new solutions for predicting concrete compressive strength. Numerous studies conducted by researchers have predicted concrete compressive strength using various methods, making significant contributions to the literature [7–58]. Particularly, models that predict concrete compressive strength with high accuracy using datasets, without the need for laboratory tests, have been developed. However, due to the heterogeneous and complex nature of concrete, many limitations remain in this field. Notably, there is a lack of in-depth and comprehensive studies among the existing research. Therefore, this study aims to examine the existing literature on the prediction of concrete compressive strength to identify trends and challenges in the field.

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To this end, studies on the prediction of concrete compressive strength from 2000 to 19th August 2024 were scanned in the Scopus Database. The artificial intelligence and machine learning methods used for predicting concrete compressive strength were examined in depth, and the most common keywords were identified. After searching for these relevant keywords in the Scopus Database, 6583 related articles were found. After a detailed examination, the most popular 2319 articles were selected. Subsequently, three scientific measurement analyses—Co-occurrence Analysis, Citation Analysis, and Bibliographic Coupling Analysis—were conducted using VOSviewer software to identify the most densely researched areas, trends, gaps, problems, relevant sources, institutions, and countries in the field of concrete compressive strength prediction.

This study, which focuses on identifying gaps in the prediction of compressive strength, thoroughly examines the existing research. The most accurate and rapid models for predicting concrete compressive strength are identified. In addition, leading studies, researchers, sources, institutions, and countries contributing to the field of concrete compressive strength prediction have been identified. Moreover, this study closely examines the limitations and recent developments in the field.

In conclusion, it is believed that efforts to improve prediction methods for concrete compressive strength, identify the most suitable prediction methods, and integrate these methods into the field are of paramount importance for improving both practical and theoretical applications. Therefore, by deepening the existing knowledge in the field of concrete compressive strength prediction, this study aims to guide future research.

2. Methodology

This study aims to identify trends, gaps, the most relevant sources, institutions, authors, and countries by examining research on the prediction of concrete compressive strength using the scientific mapping method. It also seeks to assist in making strategic decisions that will guide future research. The methodology of the study consists of several stages: data collection/selection, choosing the scientific mapping method, and applying the scientometric technique.

2.1. Detection of Keywords

A comprehensive literature review was carried out to identify commonly mentioned words in studies related to the prediction of concrete compressive strength by analyzing the abstract sections of manuscripts. Specifically, 52 SCI-indexed articles published after 1st January 2015, each having at least 50 citations as identified through the Web of Science, were examined to uncover these terms. These articles were thoroughly analyzed, and frequently mentioned keywords, which appeared more than four times, were identified and are presented in the table below.

Table 1. The common words detected in abstract sections of manuscripts.

Keywords	Number of Manuscript Containing Key Words
Compressive strength	52
Concrete	52
Predict	52
Artificial	42
ANN	32
Machine Learning	25
Adaptive Neuro Fuzzy Inference ANFIS	10
Multiple Linear Regression	9
Estimate	8
Support Vector Regression	7
Random Forest	6
Support Vector Machine	6

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AI	5
Artificial intelligence	5
Decision Tree	5
Gene Expression Programming	5
Gradient Boosting Regression	5

2.2. Detection of Relevant Documents

The following formulation is written in the advanced search engine of WoS to detect all related manuscripts fitting the formulation in the abstract section: ((TITLE-ABS-KEY (concrete) AND TITLE-ABS-KEY ("compressive strength")) AND ((TITLE-ABS-KEY (predict) OR TITLE-ABS-KEY (estimate) OR TITLE-ABS-KEY (artificial) OR TITLE-ABS-KEY ("machine learning") OR TITLE-ABS-KEY ("Multiple Linear Regression") OR TITLE-ABS-KEY ("Support Vector Regression") OR TITLE-ABS-KEY ("Random Forest") OR TITLE-ABS-KEY ("Support Vector Machine") OR TITLE-ABS-KEY ("Artificial intelligence") OR TITLE-ABS-KEY (ai) OR TITLE-ABS-KEY ("Decision Tree") OR TITLE-ABS-KEY ("Gene Expression Programming") OR TITLE-ABS-KEY ("Gradient Boosting Regression"))) AND PUBYEAR > 1999 AND PUBYEAR < 2025). Later, manuscripts which are SCI and SSCI indexed, published from 2000 to 19th August 2024 and written in English, are filtered. Later, manuscripts having document types such as articles and early access are filtered to find the most prestigious research. A total of 6583 manuscripts were detected. Subsequently, obtained documents are screened to omit irrelevant documents from the list, and 2319 documents remained. The obtained documents in the list are analyzed via VOSviewer to obtain the current research trend, research gap, the most used machine learning method to shed light on future research directions, and the most relevant journals and authors to enhance scholar connections. The flowchart outlining the methodology of the study is provided in Figure 1.

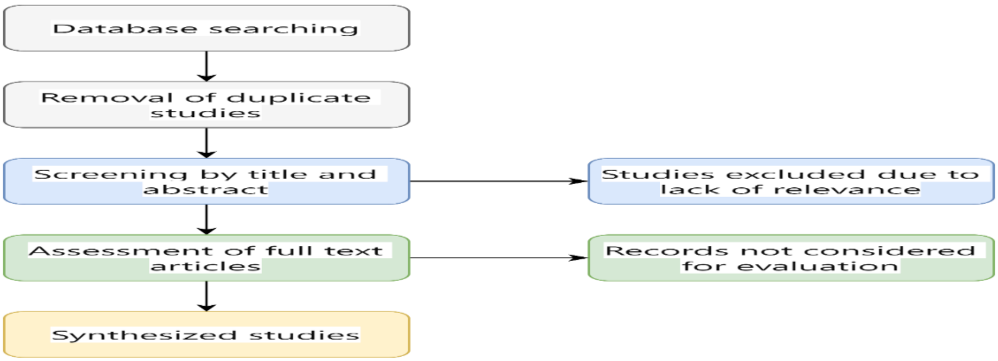

Figure 1. Flowchart describing the methodology of the study**.**

2.3. The Selection of a Science Mapping Tool

To conduct an in-depth examination of a research topic, an appropriate science mapping tool must be selected [59]. Bibliometric and scientometric analysis are widely used scientific mapping methods. While bibliometric analysis is based on literature, scientometric analysis maps the development of research based on literature [60]. Therefore, in this study, scientific articles retrieved from the Web of Science database using relevant keywords were analyzed using the VOSviewer bibliometric and scientometric mapping tool.

2.4. Bibliometric and Scientometric Techniques

Through bibliometric and scientometric analysis methods, research on the prediction of concrete compressive strength was examined to identify trends, gaps, methodologies, and the most relevant countries, institutions, and authors in the field. These analyses were conducted using VOSviewer software. To detect the most frequently repeated words in titles and abstracts, several analyses were performed, including Co-occurrence Analysis, Text-based Mapping, Citation Analysis, Bibliographic

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Coupling, and Bibliographic Data Analysis. The authors, institutions, and citation counts of the most cited articles were identified, along with the countries that published the highest number of articles on concrete compressive strength prediction. A summary of the scientometric analysis used in this study is presented in Figure 2.

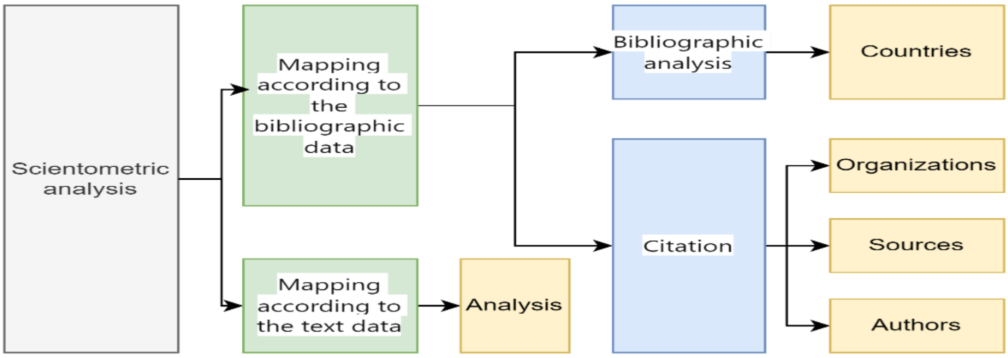

Figure 2. Summary of Bibliometric and Scientometric Analyses.

3. Findings

3.1. Density of Publications Concerning Studies on Concrete Compressive Strength Prediction

The earliest studies on the prediction of concrete compressive strength date back to the mid-20th century. From 2000 to 19th August 2024, a total of 6583 articles have been published on this topic. The distribution of the most popular 2319 articles by year is shown in Figure 3.

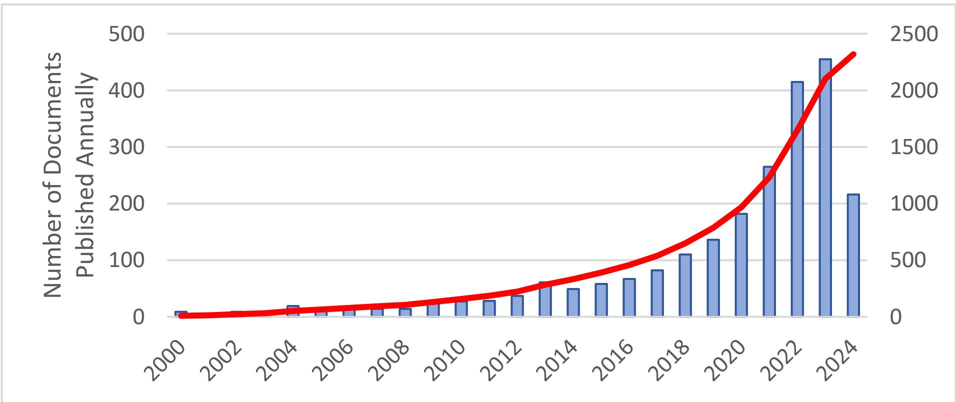

Figure 3. Distribution of Studies on Concrete Compressive Strength Prediction by Year.

In the graph, the red line represents the cumulative trend, the numbers on the left axis indicate the number of documents published annually, and the numbers on the right axis represent the cumulative total. Upon reviewing the graph, it becomes clear that studies on concrete compressive strength prediction have increased over the years. In 2000, there were 9 articles, and this number rose to 49 by 2014. Therefore, the period from 2000 to 2014 can be considered the initial phase. The years 2015–2019 represent a period of acceleration in terms of the number of articles. In 2015, there were 58 articles, followed by 67 in 2016, 82 in 2017, and 136 in 2019.

The period from 2020 to 2023 marks a significant surge in publication numbers, with a noticeable increase starting in 2020. By 2023, the number of published articles peaked at 455. This indicates a marked increase in interest in the topic, particularly after 2020. It is clear that the number of articles published in 2024 will continue to grow, with 216 articles published by 1st January to 19th August 2024, which does not yet represent the full extent of publications for the year. This growth in publication numbers shows that the topic of concrete compressive strength prediction is receiving increasing attention and that this field is expanding rapidly.

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The prediction of concrete compressive strength has become an increasingly important research area, and the rise in publication numbers is likely to continue in order to meet this growing demand **[59]**. Therefore, performing bibliometric analysis to analyze this rapidly increasing volume of data and obtain guiding insights is essential. Through such analysis, researchers and practitioners will be able to make more informed decisions regarding the prediction of concrete compressive strength.

3.2. Main Research Interests Predicting Compressive Strength

Based on the article data, the most frequently repeated keywords were extensively analyzed using VOSviewer software. During the analysis process, the minimum occurrence threshold for terms was set at 30 to identify the most commonly used keywords **[**59**]**. Among the terms that met this criterion, meaningful ones were selected, allowing for detailed evaluations of trends related to the prediction of concrete compressive strength. The relationships between the most frequently repeated keywords concerning the prediction of concrete compressive strength are illustrated in Figure 4.

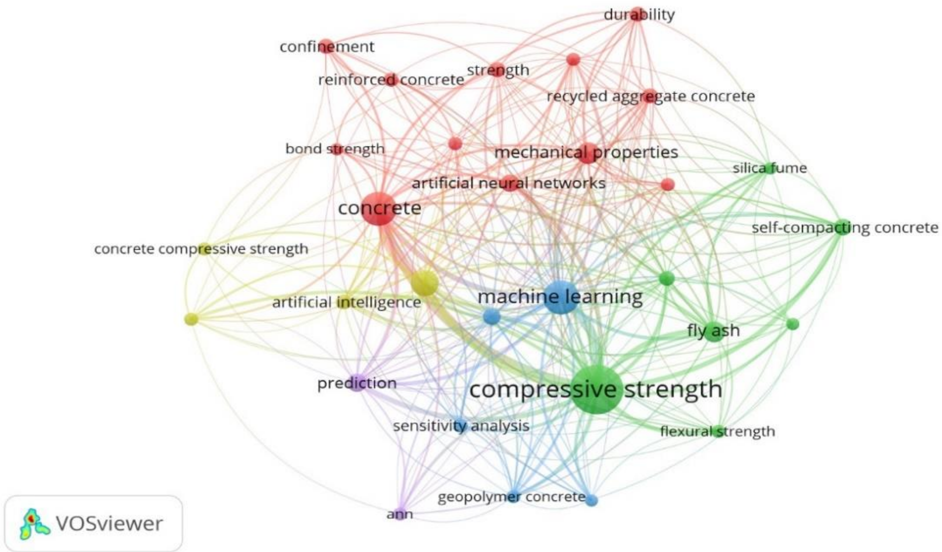

Figure 4. Mapping the words repeated in documents**.**

The colors on the map represent thematic areas where specific keyword groups are concentrated. Green represents the fundamental concepts related to concrete compressive strength; red denotes the general properties of concrete, its durability, and the use of recycled materials; blue signifies applications of artificial intelligence and machine learning; yellow highlights the relationship between artificial intelligence and concrete strength; and purple corresponds to alternative concrete materials and methods such as artificial neural networks used in their analysis.

The term 'concrete' has been addressed across a wide range of engineering problems and research topics. It shows a strong relationship, particularly with topics like 'mechanical properties' and 'durability' [61–73]. Similarly, the term 'compressive strength' stands out as one of the most critical performance metrics in concrete studies [74–85]. The large nodes for main terms like 'concrete' and 'compressive strength' being connected to many subtopics indicate that these terms are supported by an extensive literature base in concrete research [86–97]. If we assess the connection lines in Figure 4, it is evident that the terms 'concrete types' and 'mechanical properties of concrete' are directly linked to terms like 'strength', 'compressive strength', 'flexural strength', and 'shear strength'. This is because different types of concrete exhibit different mechanical performance characteristics **[**98–104**]**. The size and subject areas of the repeated keywords in the articles, categorized by research field, are provided in Table 2.

Table 2. Grouping of repeated words in articles according to research field.

ID	Keywords	Subject Areas	Occurrences	Rate (%)	Total Link Strength
1	Compressive strength	Mechanical properties of concrete	641	36.00	699
2	Mechanical properties		110		77
3	Strength		49		48
4	Flexural strength		39		59
5	Concrete compressive strength		37		20
6	Shear strength		36		25
7	Bond strength		32		30
8	Concrete	Concrete types	285	20.82	355
9	Self-compacting concrete		63		89
10	Recycled aggregate concrete		48		55
11	Reinforced concrete		41		28
12	Geopolymer concrete		39		68
13	Lightweight concrete		36		31
14	High-strength concrete		34		31
15	Machine learning	Modeling and Analysis Methods	281	31.92	368
16	Artificial neural network		156		186
17	Prediction		72		127
18	Artificial neural networks		65		88
19	Gene expression programming		62		94
20	Modeling		48		72
21	Artificial intelligence		46		80
22	Sensitivity analysis		41		55
23	Ann		35		39
24	Random forest		31		46
25	Fly ash	Pozzolanic additives	100	5.00	147
26	Silica füme		31		52
27	Durability	Durability and sustainability	47	3.13	45
28	Sustainability		35		50
29	Confinement	Other topics	47	3.13	31
30	Ultrasonic pulse velocity		35		45

As shown in Table 2, the subject areas can be categorized into six sections: mechanical properties of concrete, concrete types, modeling and analysis methods, pozzolanic additives, durability and sustainability, and other topics. These sections clearly illustrate which areas receive more attention in predicting concrete compressive strength and which methods are most frequently used.

3.3. Best Journals on Estimating Concrete Compressive Strength

For journals to be recognized as reputable and authoritative within their field, they must publish articles with a high capacity for citations. However, journals that produce a large number of articles and volumes cannot be considered authoritative in their field unless they are able to increase their citation counts. Therefore, citation analysis is important in quantifying the scientific impact of a study, journal, or researcher.

In this section of the study, the key journals publishing on the prediction of concrete compressive strength were identified through Journal, Document, and Citation analyses. For this purpose, the VOSviewer software was used, with the threshold for the number of documents per source set at 20. Out of 257 sources, 24 journals met the threshold. The mapping of journals based on citations is provided in Figure 5.

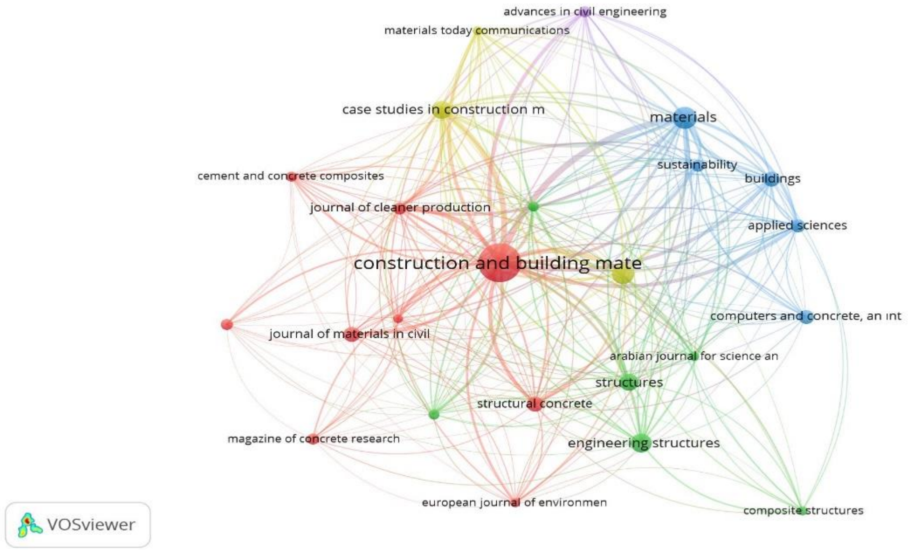

Figure 5. Mapping of journals according to citations.

The journals in the red group on the map represent those focused on construction materials; the blue group represents journals on sustainable civil engineering; the green group includes journals covering composite materials; and the purple and yellow groups represent journals related to materials science. The 'Construction and Building Materials' journal holds a central position and stands out in terms of the number of documents, citations, and total link strength compared to other journals. The journals grouped by reference patterns are provided in Table 3.

Table 3. Journals grouped by reference patterns.

ID	Journals	Documents	Citations	Total Link Strength
1	Construction and Building Materails	370	20553	1781
2	Materials	122	3565	851
3	Case Studies in Construction Materials	81	1608	582
4	Journal of Building Engineering	99	2841	549
5	Journal of Cleaner Production	36	2252	501
6	Applied Sciences	45	1296	343
7	Buildings	54	701	309
8	Structural Concrete	56	816	290
9	Neural Computing and Applications	26	1480	280
10	Structures	73	1048	253
11	Advances in Civil Engineering	31	856	242
12	Materials Today Communications	21	313	240

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13	Engineering Structures	89	3565	232
14	Sustainability	38	690	227
15	Scientific Reports	26	250	169
16	Cement and Concrete Research	21	2949	158
17	Journal of Materials in Civil Engineering	57	1669	157
18	Arabian Journal for Science and Engineering	23	310	145
19	European Journal of Environmental and Civil Engineering	22	424	128
20	Computers and Concrete, an International Journal	52	822	113
21	Cement and Concrete Composites	26	1893	108
22	Composite Structures	23	1118	76
23	Magazine of Concrete Research	29	473	56
24	Materials and Structures	34	930	48

The journal with the most articles published (370) and the highest number of citations (20553) is 'Construction and Building Materials'. In terms of total link strength, the three most important journals contributing to the field of concrete compressive strength prediction are 'Construction and Building Materials', 'Materials', and 'Case Studies in Construction Materials'. Although the 'Journal of Cleaner Production' and 'Journal of Building Engineering' have published fewer articles and received fewer citations compared to the top three journals, they stand out for their high total link strength. This indicates that the articles published in these journals have a strong interaction with other research in the field.

3.4. Key Researchers

Identifying the leading researchers in the field of concrete compressive strength prediction is of great importance, as they drive innovation and progress in this area. Therefore, in this study, analyses of Author, Document, Citation, Average Citation, and Total Link Strength were conducted to highlight the significance of authors working on concrete compressive strength prediction. To identify the most relevant sources using VOSviewer, a minimum threshold of 10 documents per author was set. Out of 6647 authors, 32 authors met the criteria, as shown in Table 4. The size of published documents by these authors is illustrated in Figure 6.

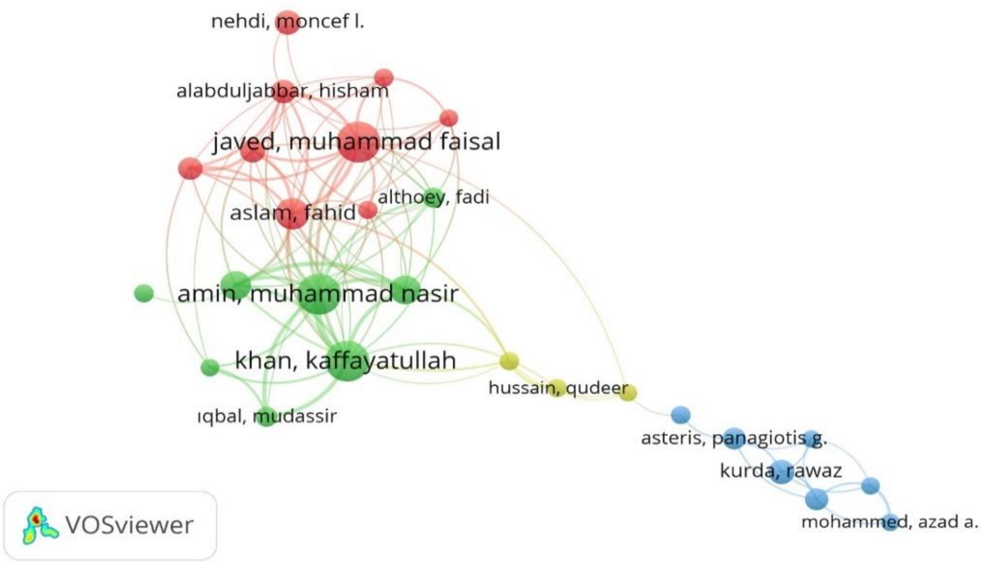

Figure 6. Size of published documents by authors.

The colors represent the average years of publications. Authors highlighted in yellow represent those who have published more recent documents, while green, blue, and purple respectively indicate authors who contributed relatively earlier to the field, based on the citation delay analysis.

Clusters of different colors represent distinct groups of researchers in the field of concrete compressive strength prediction. For instance, researchers in the red and green groups have significant collaborations. Notably, names like Muhammad Faisal Javed and Muhammad Nasir Amin stand out. The lines in the visualization represent the intensity of collaboration, while researchers located at the node positions have more influence and a broader network. The blue group stands out as a more independent cluster compared to the others. The number of articles, citations, and average citations of the authors related to concrete compressive strength prediction are provided in Table 4.

Table 4. Author citations and article information.

ID	Author	Documents	Citations	Average Citiations	Total Link Strength
1	Amin, Muhammad Nasir	36	859	23,86	96
2	Javed, Muhammad Faisal	35	1692	48,34	65
3	Khan, Kaffayatullah	35	1029	29,40	92
4	Aslam, Fahid	24	2019	84,13	62
5	Ahmad, Ayaz	21	1188	56,57	50
6	Ahmad, Waqas	21	919	43,76	56
7	Nematzadeh, Mahdi	20	640	32,00	0
8	Ly, Hai-Bang	18	981	54,50	0
9	Behnood, Ali	17	1109	65,24	9
10	Kurda, Rawaz	17	701	41,24	12
11	Nehdi, Moncef L.	17	752	44,24	2
12	Alabduljabbar, Hisham	16	697	43,56	32
13	Farooq, Furqan	16	1515	94,69	35
14	Alyousef, Rayed	15	1100	73,33	31
15	Asteris, Panagiotis G.	14	1828	130,57	8
16	Mohammed, Ahmed Salih	14	458	32,71	13
17	Althoey, Fadi	13	196	15,08	20
18	Iqbal, Mudassir	13	261	20,08	27
19	Golafshani, Emadaldin Mohammadi	12	503	41,92	9
20	Deifalla, Ahmed Farouk	11	222	20,18	14
21	Gamil, Yaser	11	81	7,36	15
22	Huang, Jiandong	11	185	16,82	1
23	Hussain, Qudeer	11	198	18,00	10
24	Joyklad, Panuwat	11	512	46,55	21
25	Samui, Pijush	11	683	62,09	3
26	Yang, Keun-Hyeok	11	99	9,00	0
27	Ahmed, Hemn Unis	10	530	53,00	12
28	Ali, Mujahid	10	147	14,70	18
29	Bahrami, Alireza	10	89	8,90	4
30	Mohammed, Azad A.	10	459	45,90	8

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31	Salami, Babatunde Abiodun	10	213	21,30	16
32	Sihag, Parveen	10	390	39,00	5

Table 4 ranks the authors based on the number of articles they have published on the prediction of concrete compressive strength. Amin, Muhammad Nasir is the author with the highest number of articles, while Aslam, Fahid has the most citations. Although Asteris, Panagiotis G. has fewer publications, he holds the highest average citation count.

3.5. Leading Organizations

The number of citations is an important criterion for evaluating the academic impact of a publication. Similarly, institutions that produce highly cited papers are typically leading and recognized academic institutions in their field. However, institutions that publish a large number of papers but receive fewer citations may indicate that their publications have not attracted significant academic attention. Citation analysis is crucial for understanding which institutions are conducting more impactful research and raising awareness in the field. Therefore, in this study, the significance of organizations involved in predicting concrete compressive strength was highlighted through analyses of Organization, Document, Citation, and Total Link Strength. For this purpose, VOSviewer was used to identify the most relevant sources, setting a minimum threshold of 10 documents per organization. Out of 4879 sources, 18 organizations met the criteria. The mapping of organizations publishing documents on the prediction of concrete compressive strength is shown in Figure 7.

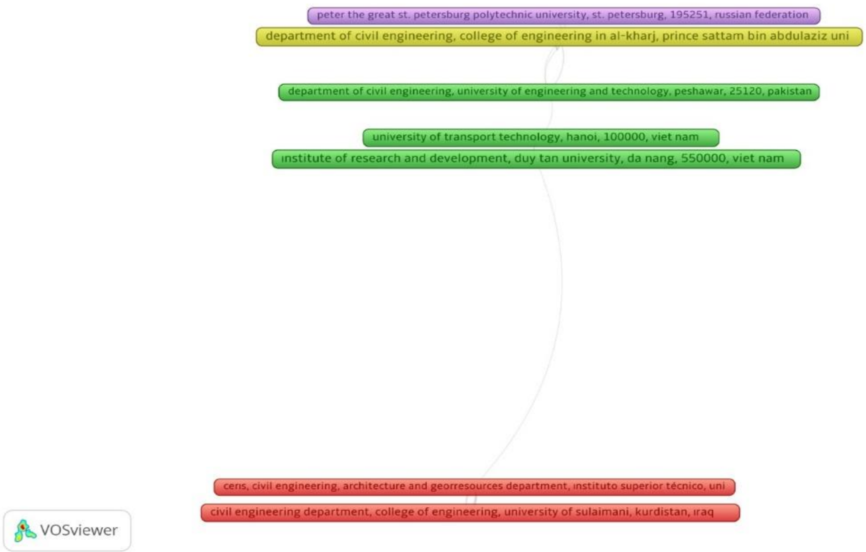

Figure 7. Mapping of organizations publishing documents on the prediction of concrete compressive strength.

The connections visible on the map represent collaborations between different universities or engineering faculties. The lines illustrate the intensity of these collaborations. Universities within the green group (such as University of Transport Technology and Duy Tan University) are engaged in national collaborations, while universities in the red group (such as Instituto Superior Técnico, Portugal, and University of Sulaimani, Iraq) are involved in international collaborations. The yellow and purple groups (such as St. Petersburg Polytechnic University, Russia, and Prince Sattam Bin Abdulaziz University, Saudi Arabia) demonstrate collaborations between geographically distant regions. The grouping of organizations according to citations is provided in Table 5.

Table 5. Grouping of organizations according to citations**.**

ID	Organization	Documents	Citations	Total Link Strength
1	Department of Civil Engineering, College of Engineering İn Al-Kharj, Prince Sattam Bin Abdulaziz University, Al-Kharj, 11942, Saudi Arabia	34	2150	26
2	Department of Civil and Environmental Engineering, College of Engineering, King Faisal University, Al-Ahsa, 31982, Saudi Arabia	27	456	25
3	Department of Civil Engineering, Comsats University Islamabad, Abbottabad, 22060, Pakistan	25	790	26
4	Institute of Research and Development, Duy Tan University, Da Nang, 550000, Viet Nam	24	1815	10
5	Department of Civil Engineering, Comsats University Islamabad, Abbottabad Campus, Abbottabad, 22060, Pakistan	21	1164	13
6	Department of Civil Engineering, University of Mazandaran, Babolsar, Iran	16	1004	0
7	Civil Engineering Department, College of Engineering, University of Sulaimani, Iraq	15	566	17
8	University of Transport Technology, Hanoi, 100000, Viet Nam	15	932	5
9	Department of Civil Engineering, College of Engineering, Najran University, Najran, Saudi Arabia	14	164	15
10	Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Viet Nam	13	772	5
11	Department of Highway and Bridge Engineering, Technical Engineering College, Erbil Polytechnic University, Erbil, 44001, Iraq	12	523	25
12	Cerıs, Civil Engineering, Architecture and Georresources Department, Instituto Superior Técnico, Universidade De Lisboa, Av. Rovisco Pais, Lisbon, 1049-001, Portugal	11	438	23
13	Department of Civil Engineering, University of Engineering and Technology, Peshawar, 25120, Pakistan	11	153	5
14	Peter the Great St. Petersburg Polytechnic University, St. Petersburg, 195251, Russian Federation	11	331	3
15	School of Civil Engineering, Harbin Institute of Technology, Harbin, 150090, China	11	441	0
16	Department of Civil Engineering, College of Engineering, Nawroz University, Duhok, 42001, Iraq	10	453	20
17	School of Civil Engineering, Guangzhou University, Guangzhou, 510006, China	10	143	2
18	School of Civil Engineering, Southeast University, Nanjing, 211189, China	10	664	0

Table 5 shows that Prince Sattam Bin Abdulaziz University leads in both the number of articles (34) and citations (2150) in the field of concrete compressive strength prediction. Other highly cited institutions include Duy Tan University, Comsats University, University of Mazandaran, and University of Transport Technology.

3.6. Key Countries

Mapping the countries conducting research on predicting concrete compressive strength contributes to a better understanding of scientific production and interactions, as well as to promoting international collaborations. Therefore, in this study, analyses of Country, Document, Citation, Average Citation, and Total Link Strength were conducted to highlight the significance of countries involved in concrete compressive strength prediction research. For this purpose, VOSviewer was used to identify the most relevant countries, with a minimum threshold of 20 documents per country. Out of 100 countries, 33 countries met the criteria. The mapping of countries publishing documents on the prediction of concrete compressive strength is shown in Figure 8.

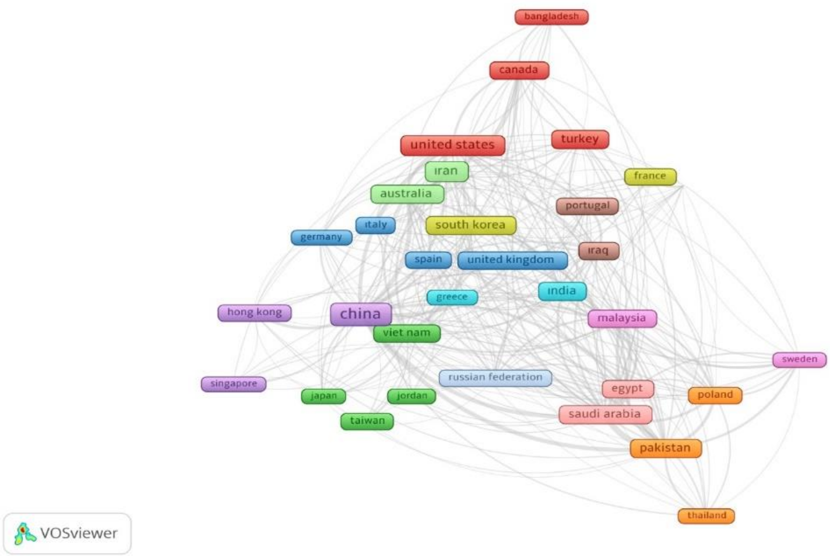

Figure 8. Mapping of countries publishing documents.

The map illustrates the network of scientific collaboration between countries. Notably, countries such as China, United States, and Iran are central to the network and maintain strong connections with many other countries. Countries within the same color group tend to collaborate intensively among themselves. The document and citation volumes by country are presented in Table 6.

Table 6. Document and citation volumes by country.

ID	Country	Documents	Citations	Total Link Strength
1	China	659	16848	404
2	Iran	270	11289	199
3	United States	243	9484	207
4	India	205	5195	123
5	Australia	179	7548	205
6	Turkey	177	8781	62
7	Saudi Arabia	169	4860	356
8	Pakistan	151	4957	314
9	South Korea	138	4687	87
10	Viet Nam	103	4865	117
11	Iraq	91	3376	115
12	Canada	89	3723	96
13	Egypt	87	1727	170
14	United Kingdom	78	4773	99
15	Malaysia	77	2977	162
16	Portugal	57	2573	51
17	Poland	56	2113	114
18	Taiwan	47	3303	15
19	Russian Federation	43	1157	82

20	Spain	40	1361	40
21	France	39	745	32
22	Hong Kong	39	1562	43
23	Italy	39	1225	38
24	Japan	35	1289	37
25	Greece	31	2265	50
26	Thailand	31	1019	40
27	Germany	30	1006	43
28	Jordan	28	503	16
29	Sweden	28	386	68
30	Singapore	27	1038	21
31	Nigeria	23	366	33
32	Algeria	22	712	25
33	Bangladesh	22	492	26

Other prominent countries include India, Australia, and Turkey. These countries hold significant positions in terms of citation and publication numbers, although their total link strength is relatively lower compared to others. Countries like Saudi Arabia, Pakistan, Vietnam, Iraq, Canada, and Egypt rank in the middle in terms of total link strength and citation counts. Countries such as Taiwan, France, Hong Kong, and Italy have lower total link strength compared to other countries. Finally, countries like Bangladesh, Algeria, and Nigeria contribute less to the scientific literature on concrete compressive strength prediction.

4. Discussion

This study, aiming to identify trends and challenges in the prediction of concrete compressive strength, conducted a comprehensive literature review using bibliometric and scientometric analysis methods through VOSviewer.

The results show that concrete compressive strength prediction is a widely researched topic across many countries, with approximately half of the publications originating from China, Iran, United States, India, Australia, and Turkey. The size of the construction industries, investments in R&D, and academic infrastructure in these countries have enabled them to conduct significant research in this field and stand out in the international literature. Between 2000 and 19th August 2024, a total of 6583 articles have been published on the prediction of concrete compressive strength, with the 'Construction and Building Materials' journal being the most prominent in terms of both publications and citations.

Upon reviewing the articles within the scope of the study, six main research areas were identified: mechanical properties of concrete, concrete types, modeling and analysis methods, pozzolanic additives, durability and sustainability, and other topics. Each area contributes to enhancing the performance, safety, and sustainability of concrete. Research on the mechanical properties under different mixture ratios, materials, curing conditions, and periods is crucial for material science. Developing special concrete types promotes innovations that allow for selecting the most suitable concrete for specific structures and improving material performance. Modeling and analysis methods are essential for predicting and optimizing compressive strength. Pozzolanic additives have the potential to enhance concrete performance, reduce its carbon footprint, and make it more environmentally friendly. Emerging topics like the use of nanomaterials in concrete and 3D-printed concrete open new doors in durability and sustainability.

Researchers have generally employed a variety of AI and machine learning methods to predict concrete compressive strength, including Multiple Linear Regression (MLR), Random Forest (RF), Support Vector Regression (SVR), Decision Tree (DT), Gradient Boosting Regression (GBR), Artificial

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Neural Networks (ANN) for deep learning, Adaptive Neuro Fuzzy Inference System (ANFIS) as a hybrid method, and Gene Expression Programming (GEP) as an evolutionary algorithm [105–120].

Artificial Intelligence (AI), by imitating human intelligence and learning capabilities, integrates these abilities into computer systems [121]. To enable AI models to predict concrete compressive strength, large datasets are required, often consisting of parameters like cement type, cement dosage, water/cement ratio, aggregate type, aggregate amount, additive amount, and curing time. After data processing, AI models are trained and used to predict compressive strength for new concrete mixtures.

MLR is a simple, fast method commonly used for predicting concrete compressive strength [122]. This method models the linear relationship between multiple independent variables affecting concrete strength and the dependent variable (compressive strength). For example, the impact of an increase in cement curing time on concrete compressive strength can be clearly observed [123]. However, MLR cannot model nonlinear and complex relationships as it is sensitive to outliers.

The RF algorithm is used to predict the compressive strength of complex, nonlinear concrete mixtures and to optimize concrete formulations [18,48,61]. Multiple decision trees are independently trained to predict compressive strength, and the predictions are then combined to reduce individual errors, producing a more accurate prediction model. This process requires more computational power and time. Model performance is measured using metrics like Mean Squared Error (MSE) and R^2 [124]. Once validated, the model can be used to predict compressive strength for new concrete mixtures.

SVR is another algorithm that predicts concrete compressive strength for nonlinear, complex datasets [118]. It uses kernel functions to capture the intricate properties of concrete components, reducing the risk of overfitting [7]. In this way, it also minimizes the risk of overfitting. The model's performance is measured using performance metrics such as MSE and R^2 [124]. Since SVR is a method with low interpretability, it is difficult to understand the impact of concrete components on concrete compressive strength.

In the DT method, rules are created based on the data [125]. Each rule splits the data into nodes and branches, modeling the relationships between factors that affect compressive strength, and determining the impact of concrete parameters on strength [117]. If the DT becomes too branched, overfitting can occur.

GBR, unlike DT, trains multiple decision tree models sequentially to improve the prediction of compressive strength [61,126]. In large datasets, this process can become lengthy, and interpreting the influence of concrete parameters on strength becomes challenging.

ANN is a method that effectively determines the influence of complex, nonlinear concrete components on compressive strength [127]. t consists of three main layers: input layer, hidden layers, and output layer [128]. Performance is measured using MSE and R^2 metrics [124]. In large datasets, overfitting and cost increases may occur.

ANFIS is a hybrid model that combines the features of ANN and Fuzzy Logic (FL) [129]. ANN is used for learning, while FL handles nonlinear relationships. Concrete parameters are converted into FL rules, and fuzzy sets are defined for the inputs. The model is optimized using ANFIS, and performance is analyzed using MSE, Mean Absolute Error (MAE), and R^2 metrics [130]. This model can predict the effects of complex and nonlinear parameters on strength, though in large datasets, computational costs and processing time may increase. Additionally, understanding which parameters affect compressive strength can become difficult.

GEP is an evolutionary algorithm that uses mathematical models and functions to predict compressive strength [13,131,132]. It handles complex concrete parameters with ease. Concrete parameters are taken as input, mathematical models are created, and these models evolve. The model's performance is evaluated through a fitness function, and its validation is checked using MSE, MAE, and R^2 metrics [130]. The trained models can more accurately predict compressive strength, allowing different concrete mix parameters to be modeled effectively. For GEP to work successfully, parameter tuning is essential, as improper tuning can lead to poor model performance.

5. Conclusions

The prediction of concrete compressive strength is a topic of significant global interest among researchers. Although many studies have been conducted on this subject, there has not been a comprehensive study that closely examines, summarizes, and monitors the latest developments while providing guidance for future research. Therefore, this study is believed to offer valuable insights for upcoming research in the field of concrete compressive strength prediction.

In the first stage of this study, the relevant keywords associated with predicting concrete compressive strength were identified. In the second stage, studies conducted between 2000 and 19th August 2024 related to concrete compressive strength prediction were retrieved from the Scopus Database. In the third stage, irrelevant studies were filtered out, and the most popular 2319 articles were selected. In the fourth stage, Co-occurrence Analysis, Citation Analysis, and Bibliographic Coupling Analysis were conducted. In the final stage, the research areas, gaps, and trends related to concrete compressive strength prediction were explained.

Moreover, the use of machine learning methods such as MLR, FL, ANN, ANFIS, SVM, SVR, RF, GBR, and GEP for predicting concrete compressive strength is crucial for understanding and correlating complex concrete parameters. Each method has its own unique advantages and disadvantages. The advantages of these models include their ability to model nonlinear relationships (ANN, SVR, and ANFIS), high accuracy and performance (ANN, RF, and GBR), simplicity and interpretability (MLR and DT), and the ability to correct errors while reducing overfitting risks (RF and GBR). On the other hand, the disadvantages include high computational costs (ANN, RF, GBR, ANFIS, and GEP), difficulty in interpretation (ANN and RF), risk of overfitting (ANN and DT), and sensitivity in parameter tuning (SVR, GBR, and GEP). For example, MLR is a fast and simple method, but it shows limited performance with complex parameters. ANN, RF, and SVR are high-performing models, but they come with high computational costs and limited interpretability of parameter relationships. GEP and ANFIS can model complex relationships with high accuracy but require more effort and time for parameter tuning.

In this context, all prediction models used to estimate concrete compressive strength have their own pros and cons. When selecting a prediction model, factors such as the size of the dataset, the complexity of the problem, computational resources, and interpretability should be considered.

In conclusion, this study is the first comprehensive work to review scientifically recognized research on predicting concrete compressive strength. It is believed that this study will guide future research in the field of concrete compressive strength prediction. Additionally, it has contributed to researchers' understanding of prediction methods for concrete compressive strength. Researchers who are selecting prediction methods for concrete compressive strength should consider the advantages and disadvantages of each method. Special attention is recommended when dealing with complex and large datasets.

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