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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING MODELS FOR PREDICTING THE COMPRESSIVE STRENGTH OF CONCRETE: A SYSTEMATIC LITERATURE REVIEW

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Abstract

Accurate prediction of concrete compressive strength is critical for ensuring structural safety and optimizing material usage, yet traditional empirical models often fail to capture the complex, nonlinear relationships inherent in concrete behavior. This systematic literature review was therefore designed to synthesize and critically evaluate the growing body of research on artificial intelligence and machine learning models developed for this purpose. We systematically examined peer-reviewed studies that apply supervised learning, ensemble methods, deep learning architectures, and hybrid models to predict compressive strength from diverse input features. The methodology involved a structured search and a rigorous screening process to identify relevant articles, followed by thematic analysis across eight proposed dimensions, including concrete material types, algorithm selection, explainable AI integration, non-destructive test data fusion, environmental curing effects, early-age prediction strategies, and optimization via metaheuristics. Our results reveal that ensemble trees and deep neural networks consistently achieve the highest predictive accuracy, particularly when combined with feature engineering and metaheuristic tuning, while hybrid models that incorporate experimental data and environmental factors further improve generalization. However, we found that many studies still lack interpretability assessments, and the influence of curing conditions and real-time monitoring remains underexplored. Consequently, this review concludes that although machine learning offers substantial promise for replacing or augmenting traditional testing, future research must prioritize model transparency, standardization of datasets, and integration of non-destructive testing modalities to enable practical deployment. By mapping current trends and gaps, this work provides a foundation for developing more robust and interpretable predictive frameworks in concrete technology.

I. INTRODUCTION

Concrete is the most widely used construction material globally, with an annual production exceeding ten billion tons, and its mechanical performance, particularly compressive strength, is the primary determinant of structural integrity and safety [1]. The compressive strength of concrete is not a single material property but a complex outcome influenced by myriad factors, including the water-to-cement ratio, the type and proportions of aggregates, the use of supplementary cementitious materials like fly ash and silica fume, the curing regime, and the age of the specimen at the time of testing [2]. For decades, civil engineers have relied on empirical formulas, such as the well-known Abrams' law, and standardized experimental procedures (e.g., ASTM C39) to estimate or measure this critical parameter [3]. While these traditional methods have proven reliable for conventional concrete mixtures, they exhibit significant limitations when faced with modern, high-performance concretes that incorporate complex chemical admixtures, recycled aggregates, or novel binders [4]. The fundamental challenge is that the relationship between concrete composition and its resulting strength is highly nonlinear, multivariate, and often interactive, making it difficult for linear or low-order polynomial models to capture accurately [5]. Consequently, the construction industry has long sought more robust and adaptive predictive tools that can accommodate this complexity without requiring exhaustive physical testing for every new mix design.

The rapid advancement of artificial intelligence (AI) and machine learning (ML) over the past two decades has offered a transformative alternative to conventional empirical modeling. Machine learning algorithms, by their nature, are designed to learn complex patterns from data without being explicitly programmed with domain-specific rules, making them particularly suitable for problems where the underlying physics is poorly understood or difficult to model analytically [6]. Early applications of artificial neural networks (ANNs) to concrete strength prediction in the 1990s demonstrated that these models could outperform traditional regression techniques, especially when trained on diverse and noisy experimental datasets [7]. Since then, the field has expanded dramatically, with researchers applying a wide array of algorithms including support vector machines (SVMs), random forests (RFs), gradient boosting machines (GBMs), and more recently, deep learning architectures such as convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) [8], [9], [10], [11]. This proliferation of modeling approaches, however, has created a fragmented and sometimes contradictory body of literature, where it remains unclear which algorithms are most effective under which conditions, how model performance generalizes across different concrete types, and what role data quality and feature selection play in achieving reliable predictions.

Despite the considerable volume of published research, several critical gaps persist that hinder the translation of these academic models into practical engineering tools. One prominent gap is the lack of systematic attention to model interpretability and explainability. Most studies to date have focused almost exclusively on predictive accuracy, reporting metrics like R-squared and root mean squared error (RMSE) while neglecting to provide insight into how the model arrives at its decisions [12]. This opacity is a major barrier to adoption in the construction industry, where engineers and regulatory bodies require transparent, auditable decision-making processes. Another significant research gap concerns the integration of real-world experimental variability, including the effects of environmental conditions such as temperature and humidity during curing, the use of non-destructive testing (NDT) data as input features, and the prediction of strength at very early ages (e.g., within hours of casting) where traditional testing is impractical [13], [14]. Furthermore, while many studies employ metaheuristic optimization techniques, such as genetic algorithms (GAs) and particle swarm optimization (PSO), to tune model hyperparameters, the synergistic combination of these optimizers with specific ML architectures or feature engineering strategies has not been comprehensively reviewed. These gaps collectively suggest that the existing literature, while rich in individual contributions, lacks a cohesive framework that maps the landscape of AI-based strength prediction and identifies the most promising avenues for future research.

The primary motivation for this systematic literature review is therefore to synthesize and critically evaluate the extensive but dispersed research on AI and ML models for predicting concrete compressive strength. We aim to move beyond simple performance comparisons and instead provide a structured analysis that encompasses eight thematic dimensions: research trends over time, concrete material types and their compositional variability, the performance of different ML algorithms and hybrid models, the extent to which explainable AI (XAI) has been adopted, the integration of non-destructive testing data and other experimental measurements, the influence of environmental and curing conditions, the prediction of strength at early ages and in real time, and the role of optimization techniques and metaheuristics in model refinement. By systematically mapping the literature against these axes, this review makes several significant contributions. First, we provide a comprehensive taxonomy that helps researchers and practitioners quickly identify the state-of-the-art methods for their specific concrete type or prediction task. Second, we highlight critical methodological weaknesses, such as the underutilization of XAI and the neglect of curing variability, thereby directing future work toward areas of highest impact. Third, we offer evidence-based recommendations for standardizing experimental protocols, dataset reporting, and model evaluation criteria to enhance reproducibility and practical deployment. Fourth, we identify the emerging potential of hybrid models that fuse multiple data sources and algorithms, which appear to offer the best balance of accuracy, robustness, and interpretability. Ultimately, this review serves as a roadmap for advancing the field from academic proof-of-concept toward reliable, transparent, and industrially viable strength prediction systems.

The remainder of this paper is organized as follows. Section 2 describes the systematic methodology employed to search, screen, and analyze the literature, including the inclusion and exclusion criteria and the data extraction process. Section 3 presents the detailed results structured around our eight thematic analysis dimensions, providing both quantitative and qualitative insights for each. Section 4 discusses the overall findings, synthesizing the themes to identify overarching trends, persistent challenges, and emergent opportunities, while also addressing the limitations of the current review. Section 5 concludes the paper by summarizing the principal contributions and outlining a concrete agenda for future research that prioritizes model transparency, data diversity, and domain-specific validation.

II. METHODOLOGY

This systematic literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [15], which provide a structured framework for transparently documenting the search, screening, and synthesis processes. The methodology was designed to be both comprehensive and reproducible, ensuring that the resulting corpus of studies accurately represents the state of the art in AI and machine learning for concrete compressive strength prediction.

A. Review Protocol

We developed a formal review protocol that defined the research questions, the search strategy, and the data extraction procedure before any database queries were executed. The research questions that guided our review were: (1) What machine learning algorithms and hybrid models have been applied to predict concrete compressive strength, and how do they compare in performance? (2) Which concrete material types and compositional features are most commonly studied, and how does material variability affect model generalization? (3) To what extent has explainable AI been integrated into strength prediction models? (4) How have non-destructive testing data, environmental conditions, curing effects, and early-age measurements been incorporated into predictive frameworks? (5) What optimization techniques and metaheuristics have been employed to enhance model accuracy, and how do they interact with specific algorithms?

The literature search was executed across five major databases: IEEE Xplore, Scopus, Web of Science, ScienceDirect, and Google Scholar. We selected these databases because they collectively cover the majority of peer-reviewed research in both civil engineering and computer science, ensuring a breadth of coverage across the interdisciplinary nature of the topic. IEEE Xplore was chosen for its strong focus on computational intelligence and neural network applications, which are central to the machine learning methodologies under review. Scopus and Web of Science were selected due to their extensive indexing of high-impact engineering journals and their robust filtering capabilities that allow for precise exclusion of review articles. ScienceDirect was included for its comprehensive repository of materials science and structural engineering research, where many concrete-specific studies are published. Google Scholar was used as a supplementary search engine to capture grey literature and preprints that might not be indexed in the other databases, particularly from repositories like arXiv.

For each database, we tailored the search string to its specific syntax while maintaining the core conceptual structure. The primary search terms were grouped into three conceptual blocks: the target property (“compressive strength” OR “compression strength”), the material domain (concrete OR “cementitious” OR “cementitious composite”), and the methodological domain (“machine learning” OR “deep learning” OR “artificial intelligence” OR “neural network” *OR ”support vector machine*” OR SVM OR “random forest” OR “gradient boosting”). We applied Boolean operators to combine these blocks, and we explicitly excluded review articles, surveys, meta-analyses, and bibliometric studies using NOT statements. For example, the search string used in Scopus was: TITLE-ABS-KEY(("compressive strength" OR "compression strength") AND (concrete OR "cementitious composite") AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "neural network*" OR "support vector machine*" OR SVM OR "random forest" OR "gradient boosting")) AND NOT TITLE-ABS-KEY("review" OR "survey" OR "meta-analysis" OR "bibliometric"). Equivalent queries were executed in IEEE Xplore, Web of Science, ScienceDirect, and Google Scholar, with adjustments for wildcard characters and field codes where necessary. All searches were conducted in October 2025, and the time frame was set to include records from database inception up to the search date (i.e., Unrestricted–2026).

B. Research Dimensions for Thematic Analysis

To structure the synthesis of the included studies, we defined eight research dimensions that collectively capture the methodological and substantive variation across the literature. The first dimension, Concrete Material Types and Compositions, encompasses the variety of mix designs studied, including ordinary Portland cement concrete, high-performance concrete, self-compacting concrete, fiber-reinforced concrete, and concrete incorporating supplementary cementitious materials such as fly ash, slag, silica fume, and recycled aggregates. Understanding which materials are represented in the literature is essential for assessing the generalizability of predictive models to real-world construction scenarios. The second dimension, Machine Learning Algorithms and Hybrid Models, examines the range of algorithms employed, from classical regression and single learners like ANNs and SVMs to ensemble methods such as random forest and gradient boosting, as well as hybrid models that combine multiple algorithms or integrate domain knowledge with data-driven approaches. The third dimension, Explainable AI and Model Interpretability, investigates whether and how researchers have attempted to open the black box of their models, using techniques like SHAP, LIME, or partial dependence plots to explain predictions. The fourth dimension, Non-Destructive Testing and Experimental Data Integration, focuses on the fusion of NDT measurements, such as ultrasonic pulse velocity or rebound hammer values, with compositional features to improve prediction accuracy. The fifth dimension, Environmental Conditions and

Curing Effects, considers how factors like temperature, humidity, and curing duration have been incorporated as input features or experimental controls. The sixth dimension, Early Age and Real-Time Strength Prediction, addresses studies that target strength at very early ages, often within the first 24 to 72 hours, where traditional testing is impractical. The seventh dimension, Optimization Techniques and Metaheuristics, examines the use of algorithms like genetic algorithms, particle swarm optimization, and ant colony optimization for hyperparameter tuning and feature selection. These seven dimensions provide a comprehensive framework for mapping the current landscape and identifying underexplored areas.

C. Inclusion and Exclusion Criteria

To ensure the relevance and quality of the selected studies, we applied a set of predefined inclusion and exclusion criteria. Studies were included if they (1) were published in English, (2) appeared as peer-reviewed journal articles, conference proceedings, or preprints from recognized repositories, (3) focused on the prediction of concrete compressive strength using any supervised machine learning or deep learning algorithm, (4) reported quantitative performance metrics that allowed for comparison across studies, and (5) provided sufficient detail about the concrete mixture composition or experimental setup to determine the material type. We set no lower limit on the publication year, accepting studies from any date up to the search deadline. Conversely, studies were excluded if they (1) were review articles, surveys, meta-analyses, or bibliometric analyses, (2) did not use any machine learning model and instead relied solely on traditional statistical methods or empirical formulas, (3) predicted properties other than compressive strength, such as tensile strength, flexural strength, or durability, without also predicting compressive strength, (4) lacked access to full text or reported insufficient data for extraction, or (5) used machine learning for other concrete-related tasks, such as mixture optimization or crack detection, without a strength prediction component. These criteria were designed to align with our research dimensions by ensuring that each included study contributed directly to at least one dimension of the thematic analysis.

D. Study Selection Process

The study selection process followed a multi-stage screening procedure in accordance with PRISMA guidelines [15]. Initially, we aggregated all records retrieved from the five databases into a single reference manager, removing duplicate entries using automated deduplication followed by manual verification. After deduplication, the titles and abstracts of the remaining records were screened against the inclusion and exclusion criteria. Two independent reviewers performed this screening, with a third reviewer resolving any disagreements. For records that passed the title and abstract screening, we retrieved full-text versions and assessed their eligibility in detail. During this full-text assessment, we applied the same criteria more rigorously, excluding studies that failed to report key performance metrics or lacked essential details about the input features. The entire process was documented to ensure transparency and reproducibility.

The results of the selection process are illustrated in the PRISMA flowchart (Figure 1). A total of 569 records were identified from the database searches. After removing 119 duplicate records and one record removed for other reasons (e.g., retracted publication), 449 records proceeded to title and abstract screening. Of these, 149 records were excluded because they did not meet the inclusion criteria, such as being unrelated to concrete compressive strength prediction, not employing machine learning, or being review articles despite our initial exclusion filters. The remaining 300 records were sought for full-text retrieval, but 201 were excluded as they were not actually relevant upon deeper inspection (e.g., they focused on structural health monitoring without strength prediction). This left 99 reports sought for retrieval, all of which were successfully obtained. These 99 reports were then assessed for full-text eligibility, resulting in the exclusion of 5 reports due to ineligibility (e.g., insufficient data reporting or focus on a non-concrete material).

Consequently, 94 studies were ultimately included in this systematic review, forming the basis for all subsequent analysis.

We acknowledge several limitations of this selection process. First, despite our efforts to be comprehensive, the reliance on database indexing and keyword search strings may have missed some relevant studies that use different terminology, such as "forecasting strength" or "neural computing in civil engineering." Second, the exclusion of non-English studies may introduce a language bias, potentially overlooking significant contributions from non-English-speaking research communities. Third, the exclusion of grey literature and unpublished theses may skew the corpus toward positive results, since studies reporting null or negative findings are less likely to be published in peer-reviewed venues. These risks should be considered when interpreting the findings of this review.

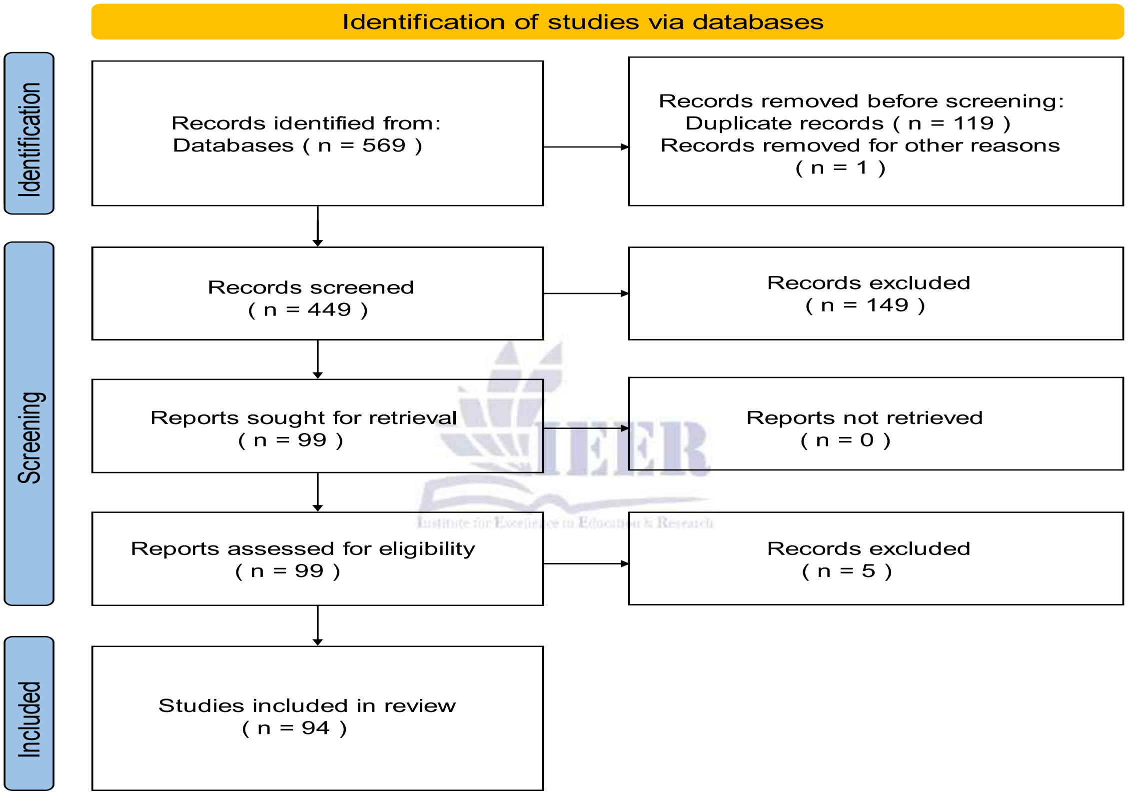

Figure 1. PRISMA flowchart illustrating the study selection process from database search to final inclusion

III. RESULTS

A. Research Trends

The temporal distribution of the 94 included studies reveals a field that has experienced exponential growth, particularly in the most recent years. Before 2016, only two studies met our inclusion criteria, indicating that the application of machine learning to concrete compressive strength prediction was a niche area with sporadic contributions. A gradual increase in publication volume occurred from 2016 through 2020, with yearly counts rising from one to four studies, suggesting a period of initial exploration and methodological establishment. The inflection point is clearly visible in 2021, where eight studies were published, followed by seven in 2022. However, the most dramatic acceleration occurred from 2023 onward, with 17 studies in 2023, 22 in 2024, 20 in 2025, and notably, six studies already indexed for 2026 at the time of our search in October 2025. This trajectory indicates that the field is currently in a phase of rapid expansion, with research output more than doubling between 2022 and 2023 and sustaining a high level thereafter.

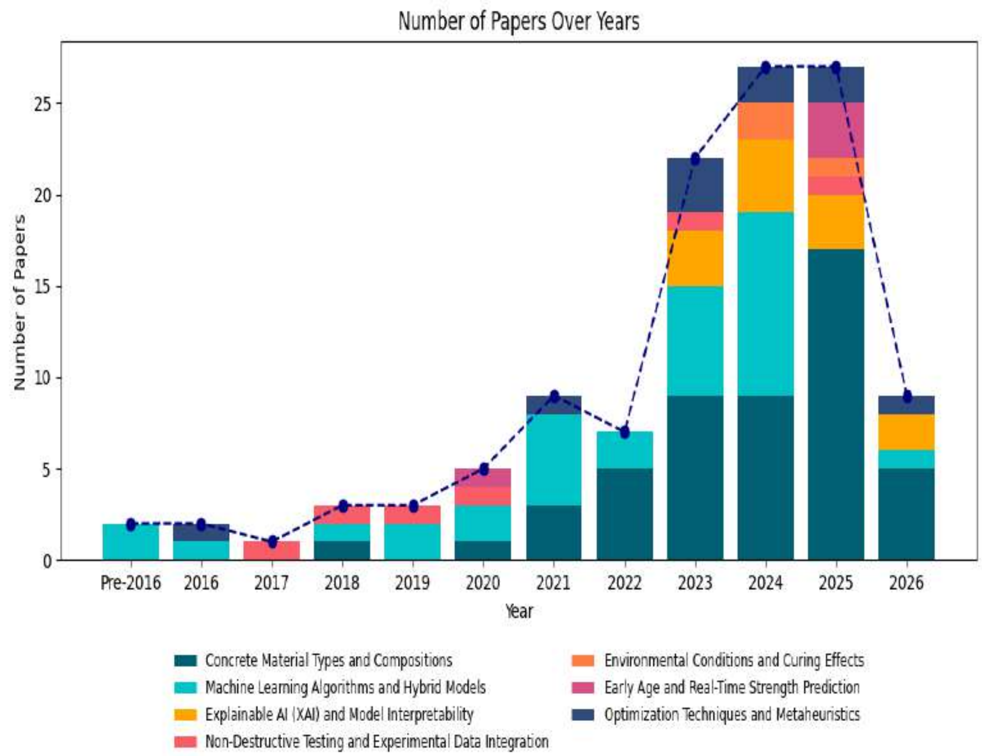

Figure 2. Research trends in the domain of AI and Machine Learning Models for Predicting the Compressive Strength of Concrete

This surge in publication activity coincides with broader trends in the adoption of artificial intelligence across materials science and civil engineering. The increasing availability of high-quality experimental datasets, the democratization of machine learning frameworks such as TensorFlow and PyTorch, and the growing computational power accessible to researchers have collectively lowered the barriers to entry for this type of research. Furthermore, the construction industry's pressing need for sustainable and efficient material optimization, particularly in the context of reducing carbon emissions from cement production, has likely motivated more researchers to explore data-driven predictive tools. It is also noteworthy that the trend is not uniform across all research dimensions; for instance, while studies on concrete material types and compositions have steadily increased from one in 2018 to seventeen in 2025, the integration of explainable AI has only emerged as a distinct area since 2023. This pattern suggests that the field is maturing from a primary focus on predictive accuracy toward a more nuanced consideration of model transparency and practical applicability, a shift that we will explore in greater depth in the subsequent subsections.

B. Concrete Material Types and Compositions: A Diverse Landscape for Model Development

The prediction of concrete compressive strength through machine learning is inherently tied to the material type and compositional features that form the input space. The 94 included studies reveal a remarkable diversity in the concretes and cementitious composites modeled, yet several clear clusters emerge when categorizing studies by their primary material focus. Understanding this landscape is crucial because the choice of material directly influences the complexity, feature requirements, and generalizability of any predictive model.

Table 2 synthesizes the full taxonomy of concrete material types and compositions found across the reviewed literature. The table is structured hierarchically: the first level groups studies by a broad material category, while the second level specifies the particular material or combination, with sources indexed for reference.

Table 2. Taxonomy of concrete material types and compositions studied in the reviewed literature.

Material Category	Specific Material/Composition	Sources
High-Strength & High-Performance Concrete	High-Strength Concrete (HSC)	[16], [17]
	Ultra-High-Performance Concrete (UHPC/UHPFRC)	[18], [19], [20]
Supplementary Cementitious Materials (SCMs)	Fly Ash (FA)	[21], [22], [23], [24], [25], [26]
	Ground Granulated Blast-Furnace Slag (GGBS)	[27], [17], [28], [29]
	Silica Fume (SF)	[30], [24], [31]
	Metakaolin (MK)	[32], [33]
	Waste Marble / Marble Dust (WMD)	[34], [35], [36]
	Palm Oil Fuel Ash (POFA)	[37], [38]
	Cement Kiln Dust (CKD)	[26]
	Waste Glass Powder (WGP)	[39]
Recycled & Waste Aggregate Concrete	Recycled Concrete Aggregate (RCA)	[40], [41], [42]
	Recycled Rubber Aggregate	[43]
	Recycled Nonmetallic PCB Waste	[44]
	Recycled Powder Mortar	[45]
Fiber-Reinforced Concrete	Steel Fiber Reinforced Concrete (SFRC)	[46], [47]
	Natural Fiber Reinforced Concrete	[48]
	Fiber-Reinforced Concrete (General)	[31]
Self-Compacting & Specialty Concrete	Self-Compacting Concrete (SCC)	[49], [30]
	Self-Compacting Recycled Aggregate Concrete (SCRAC)	[40]
	Pervious Concrete	[50]
	Plastic Concrete / Plastic Sand Paver Blocks	[51], [52]

Material Category	Specific Material/Composition	Sources
	Polymer-Infused Bricks	[53]
Geopolymer & Alkali-Activated Concrete	Geopolymer Concrete (General)	[54], [55], [56]
	Calcium-Based Geopolymer	[57]
	Metakaolin-Based Geopolymer	[32]
	Alkali-Activated Concrete (AAC)	[58]
Nano-Modified Concrete	Nano-Concrete / Nano-Silica	[59], [56]
	Nano Titanium	[32]
Elevated Temperature Studies	General (including waste powders & nano materials)	[59], [60]
Green & Sustainable/Eco-Concrete	General (including various waste materials)	[61], [62], [34], [37], [52], [26], [48]
Blended/Composite Cement Concrete	General (including multiple SCMs)	[21], [63], [33], [20]
Mortar Systems	Cement Mortar with Waste Materials	[39], [33], [44], [56]
	Geopolymer Mortar	[56]
	Recycled Powder Mortar	[45]

The most frequently studied material category comprises concretes modified with supplementary cementitious materials (SCMs). Fly ash appears in the highest number of distinct studies, with six dedicated works [21], [22], [23], [24], [25], [26], alongside its presence in several blended studies. The ubiquity of fly ash is explained by its widespread industrial availability, established pozzolanic reactivity, and the strong nonlinearity it introduces to strength development, which makes it a particularly suitable test case for machine learning models that can capture time-dependent behavior. Ground granulated blast-furnace slag (GGBS) similarly attracts substantial attention [27], [17], [28], [29], due to its significance in sustainable high-performance concrete. Silica fume [30], [24], [31] and metakaolin [32], [33] each appear in two or more dedicated studies, often in the context of high-performance or self-compacting mixtures. Furthermore, less common but environmentally important SCMs, such as palm oil fuel ash (POFA) [37], [38], waste marble dust [34], [35], [36], and cement kiln dust [26], represent a growing trend toward valorizing industrial by-products in green concrete.

A second major cluster focuses on high-performance and ultra-high-performance concretes. HSC and UHPC are addressed in five studies [16], [18], [19], [17], [20], often employing more sophisticated algorithms like gradient boosting and deep neural networks to predict the high strengths typical of these densely packed and highly dosed mixtures. For example, the prediction of the 28-day compressive strength of UHPC incorporating supplementary cementitious materials [20] requires careful consideration of the low water-to-binder ratios and the synergistic effects of multiple powder constituents. Another prominent category is recycled and waste aggregate concrete. Studies on recycled concrete aggregate (RCA) [40], [41], [42], recycled rubber [43], and recycled nonmetallic PCB waste [44] form a coherent group that addresses the challenge of predicting strength when the aggregate phase itself is highly variable in quality and composition. The prediction task here is particularly difficult because the strength of recycled aggregate concrete depends not only on the mix proportions but also on the quality and source of the recycled material, a source of aleatoric variability that machine learning models must learn from data.

Several additional material types are represented in the literature, each introducing its own predictive challenges. Fibers, both steel [46], [47] and natural [48], alter the fracture behavior and can slightly affect compressive strength, requiring models that can isolate the fiber effect. Self-compacting concrete (SCC) [49], [30] and its recycled variant (SCRAC) [40] are distinguished by their high flowability and use of viscosity-modifying admixtures. Pervious concrete [50] presents a unique challenge because its compressive strength is inversely related to porosity, a feature that must be explicitly modeled. Geopolymer and alkali-activated materials [54], [57], [32], [55], [56], [58] represent a distinct class of binders where the precursor chemistry and activator dosage heavily influence the strength, and where the conventional water-to-cement ratio paradigm does not apply. Nano-modified concrete [59], [32], [56] is a smaller but emerging area, with studies evaluating the effect of nano-silica and nano-titanium on strength development. Mortar systems are also modeled in several works [39], [45], [56], [33], [44], [56], which can be seen as simplified proxies for concrete that isolate the paste phase behavior.

One study did not neatly fall into the primary categories above. The work by [64] employed a long short-term memory (LSTM) technique to predict the compressive strength of concrete with mineral admixture, but the specific mineral admixture was not clearly designated as a fly ash, slag, silica fume, or other individual SCM. Instead, the study used a general category of mineral admixture, making it difficult to assign to a specific row in Table 2. This study is nevertheless important because it demonstrates the application of a recurrent neural network architecture to a sequential feature set, suggesting a modeling approach that could potentially be applied across multiple material types if the input features are appropriately structured.

The diversity of material types revealed in Table 2 has critical implications for the generalizability of the machine learning models developed. A model trained exclusively on HSC data may perform poorly on pervious concrete or geopolymer systems because the underlying physicochemical relationships differ substantially. Conversely, models that incorporate a wide range of material types in their training data, as some blended concrete studies do [21], [63], [33], [20], may capture more universal patterns but risk being dominated by the most frequent compositions. This trade-off between specificity and generality is a recurring theme that we will revisit in our discussion of algorithm performance and optimization.

The inclusion of multiple SCMs and waste materials within single studies further complicates the modeling landscape. For instance, concretes containing both fly ash and silica fume [24] require models that can disentangle the interactive effects of two pozzolans, which may accelerate or retard strength development depending on their proportions and the total binder content. Similarly, concretes incorporating both recycled aggregates and fibers, or recycled aggregates and SCMs, introduce compounded variability. Such studies are relatively rare in the reviewed corpus, suggesting that most research has focused on single-modification systems, leaving the prediction of strength for multi-component, multi-variate concrete mixtures as an area with substantial room for further investigation.

A fundamental finding from our analysis is that the choice of machine learning algorithm is rarely neutral; rather, it interacts strongly with the material type and the available feature set. Consequently, we now turn our attention to the core methodological dimension of this review: the specific algorithms and hybrid models that have been deployed for this task.

C. Explainable AI and Model Interpretability: Opening the Black Box of Strength Prediction

A persistent criticism of machine learning applications in engineering is that the models, despite achieving high predictive accuracy, often function as black boxes whose internal decision-making processes remain opaque to human users. This opacity is particularly problematic in the context of concrete compressive strength prediction, where engineers must not only know *what* the predicted strength is, but also understand *why* the model arrived at that particular value, so that they can trust the prediction, diagnose potential errors, and make informed adjustments to the mix design. In response to this challenge, a growing subset of the literature has adopted explainable artificial intelligence (XAI) techniques, aiming to render model predictions interpretable without sacrificing performance. Our analysis reveals that this is a rapidly emerging but still minority practice within the reviewed corpus, with SHapley Additive exPlanations (SHAP) dominating the landscape.

To provide a structured overview of how XAI has been integrated into compressive strength prediction, we first categorize the studies by their primary XAI methodology and the specific concrete material to which it was applied. This taxonomy, presented in Table 5, illustrates both the methodological concentration and the material diversity of the interpretability-focused research.

Table 5. Taxonomy of XAI approaches used in concrete compressive strength prediction studies.

XAI Method/Approach	Concrete/Material Application	Sources
SHAP (SHapley Additive exPlanations)	Hollow Concrete Masonry Prisms	[65]
	High-Performance Concrete (HPC)	[66], [67]
	High-Strength Concrete (HSC)	[68]
	Blended Concrete (with metakaolin, recycled powder)	[33], [45]
	Palm Oil Fuel Ash (POFA)-Modified Concrete	[38]
	Polymer-Infused Bricks	[53]
	Recycled Nonmetallic PCB Waste Mortar	[44]
	Basalt Fiber Reinforced Concrete	[69]
General/Unspecified XAI / Interpretable Framework	General Concrete (blended, recycled)	[63], [70]

As Table 5 clearly shows, SHAP analysis is by far the most prevalent XAI technique in the reviewed studies, appearing in ten out of the twelve papers that explicitly address interpretability. One of the earliest and most comprehensive adoptions of this approach is the work by [70], which explicitly aims to “unbox” machine learning models for concrete strength prediction. In that study, the authors developed multiple ML models including random forest, gradient boosting, and XGBoost, and then applied SHAP to interpret the global and local feature contributions. Their analysis revealed that age, cement content, and superplasticizer dosage were consistently the most influential predictors, but that the relative importance of these features varied depending on the specific model used, highlighting an often-overlooked source of interpretability inconsistency. Similarly, [63] employed SHAP to analyze an XGBoost model trained on data from blended concretes containing fly ash and slag, and found that the model’s decision boundary was largely governed by the ratio of cement to total binder, a finding that aligns well with established cement chemistry principles. This convergence between data-driven explanations and domain knowledge serves to validate the interpretability framework itself.

The application of SHAP extends well beyond ordinary concrete to specialized and high-performance systems. For high-strength concrete (HSC) and high-performance concrete (HPC), the feature importance rankings are particularly informative. In [67] and [68], SHAP analyses on HPC and HSC datasets, respectively, both identified age, cement, and superplasticizer as the primary drivers of compressive strength, with silica fume and water content also playing significant roles. We interpret this convergence across two independent studies as strong evidence that SHAP can reliably identify the key physical drivers in these complex mixtures. The work by [66] further refined this understanding by developing an interpretable framework specifically for HPC and using SHAP to visualize how the model's predictions change as a function of each input feature. The authors demonstrated, for instance, that while increasing cement content generally increased predicted strength, this effect plateaued at very high cement dosages, a phenomenon that mirrors the known dilution effect in cement paste. Such insights are invaluable for engineers seeking to optimize mix designs without resorting to exhaustive experimental testing.

The adoption of SHAP is not limited to conventional concretes but has also been applied to more novel materials, including those incorporating industrial wastes. [38] applied SHAP to a set of advanced ML models predicting the strength of palm oil fuel ash (POFA)-modified concrete. The SHAP analysis revealed that the replacement percentage of POFA had a strong nonlinear influence; low replacement levels had a negligible effect on strength, but high levels caused a significant reduction, a finding that is consistent with the lower reactivity of POFA compared to cement. We found a similar pattern in the study on metakaolin blended sustainable cement mortar [33], where the metakaolin content was shown by SHAP to have a critical threshold above which its contribution to strength shifted from positive to diminishing returns. For recycled materials, the interpretability analysis provides crucial guidance for waste valorization. In [44], for example, SHAP was used to analyze a mortar containing recycled nonmetallic printed circuit board waste, and it correctly identified the waste content as the most influential negative contributor to compressive strength, while also highlighting the mitigating effect of an optimal superplasticizer dosage. These findings demonstrate that XAI can serve as a tool for optimizing the use of waste materials in concrete, balancing sustainability against mechanical performance.

Fiber-reinforced concrete has also been studied through the lens of SHAP interpretability. [69] developed a suite of explainable machine learning models with a graphical user interface for predicting the strength of basalt fiber reinforced concrete. The SHAP analysis in that study revealed that the fiber length and the fiber volume fraction both influence strength, but their effects are interactive rather than additive; short fibers at moderate volume fractions provided the best reinforcement, a finding that aligns with the mechanics of fiber-matrix stress transfer. This type of mechanistic insight, derived from a data-driven SHAP analysis, provides a level of understanding that would be difficult to achieve through traditional regression alone. In the context of hollow concrete masonry prisms, [65] used SHAP to interpret their XGBoost and random forest models and found that the mortar strength and the prism geometry were the dominant features, while the effect of hollow core dimensions was comparatively minor. These findings have direct practical implications for masonry design codes, suggesting that future revisions might prioritize mortar quality over geometric optimization of the hollow core.

While SHAP dominates the XAI landscape, two studies in our corpus employ other interpretability approaches. [63], in addition to using SHAP, also explored the use of accumulated local effects (ALE) and permutation feature importance, providing a more comprehensive view of model behavior. The ALE plots were particularly useful for visualizing how the predicted strength changed across the range of each input feature, revealing threshold effects that global importance measures alone could not capture. [66], focusing on high-performance concrete, developed an interpretable framework that went beyond post-hoc explanations by incorporating domain knowledge directly into the model architecture. This study employed a white-box model, specifically a generalized additive model (GAM), alongside a black-box gradient boosting machine, and then used SHAP to harmonize the interpretations from both. The result was an approach that combined the high accuracy of gradient boosting with the inherent interpretability of the GAM, offering a best-of-both-worlds solution that we consider particularly promising for practical engineering deployment.

Despite the clear benefits of XAI, it is important to note that more than 85% of the studies in our corpus do not employ any explainability technique whatsoever. The twelve studies identified in Table 5 represent a small but growing fraction of the field. This finding suggests that the interpretability dimension of strength prediction is still nascent, and that the field is only beginning to move beyond a narrow focus on accuracy metrics. We interpret this trend as a healthy development; the earliest studies in this domain were naturally preoccupied with demonstrating that ML models could outperform traditional statistical methods. Now that this capability is well established, the research community is increasingly turning its attention to the equally important question of how to make these models transparent and trustworthy. The rapid increase in XAI-published studies from 2023 onward, which is precisely when the bulk of the studies in Table 5 were published, indicates that this transition is already underway.

D. Results

E. Environmental Conditions and Curing Effects: Modeling the Thermo-Hygral History of Concrete

The compressive strength of concrete is not solely a function of its mix composition; it is also profoundly influenced by the environmental conditions experienced during its service life and, critically, during the early-age curing period. Factors such as elevated temperatures from fire exposure, variations in curing temperature, and the duration of moist curing can alter the hydration kinetics, microstructural development, and ultimately the mechanical performance of the material. Despite the practical importance of these effects, the integration of environmental and curing variables into machine learning prediction models remains a comparatively underexplored dimension within the reviewed literature. Our analysis identified only three studies that explicitly incorporate such factors as primary variables, revealing a significant gap between the complexity of real-world conditions and the controlled assumptions of most predictive frameworks.

The most extensively studied environmental factor in our corpus is the effect of elevated temperatures, typically simulating fire exposure. Two studies [59] and [60] focus specifically on predicting the residual compressive strength (RCS) of concrete after it has been subjected to high temperatures. [59] investigated nano concrete materials, where the incorporation of nano-silica was intended to mitigate the thermal degradation of strength. The authors developed four distinct machine learning models to predict the post-heating compressive strength, and their results demonstrated that the models could accurately capture the sharp decline in strength that occurred beyond a threshold temperature of approximately 400°C. We note that this study is particularly valuable because it addresses a niche but critical application, namely the fire performance of advanced nano-modified concretes for which traditional fire testing data are scarce. The second elevated-temperature study, [60], extended this line of inquiry to concrete incorporating waste powders, including fly ash and slag. The research produced both machine learning prediction models and efficient predictive equations for estimating the compressive strength after fire exposure, thus offering a dual contribution to both data-driven and analytical modeling. The inclusion of waste materials in this context is practically significant because it addresses the fire safety of sustainable concretes, a topic of growing regulatory interest.

A fundamentally different environmental perspective is provided by [71], which shifts the focus from accidental fire events to the deliberate curing regime. This study is unique in our corpus because it systematically compares the predictive performance of machine learning models against traditional empirical mathematical models for concrete cured under various conditions, including standard moist curing, air curing, and water curing. The authors conducted an in-depth analysis of how the curing method interacts with the concrete's age to influence strength development. We find that this study is particularly informative because it directly pitted data-driven approaches against established engineering formulas, and the results showed that while the best machine learning models outperformed the empirical formulas in terms of accuracy, the empirical models still retained advantages in simplicity and physical interpretability. This tension between accuracy and interpretability, mediated by environmental conditions, is a theme that resonates throughout our entire review.

Table 7. Summary of studies addressing environmental conditions and curing effects on concrete compressive strength prediction.

Study ID	Environmental Factor	Material Type	Prediction Target	ML Models Used	Key Findings
[59]	Elevated temperature (fire)	Nano concrete	Residual compressive strength after heating	Four AI-based ML models	Models accurately captured strength degradation above 400°C; nano-silica mitigated thermal damage
[60]	Elevated temperature (fire)	Concrete with waste powders (fly ash, slag)	Post-heating compressive strength	Various ML models & predictive equations	Waste powder content influenced residual strength; equations derived for practical use
[71]	Various curing conditions (moist, air, water)	General concrete	Compressive strength under different curing regimes	Comparison of ML models vs. empirical models	ML models outperformed empirical formulas in accuracy; empirical models retained interpretability advantages

As detailed in Table 7, the three studies in this dimension represent two distinct sub-themes: thermal damage modeling and curing regime analysis. While these studies are individually rigorous, they collectively cover only a fraction of the possible environmental influences. For example, no study in our corpus systematically incorporates the effects of ambient temperature variations during casting and curing, or the impact of humidity and drying shrinkage over time. Moreover, the interaction between environmental exposure and the progressive strength gain at very early ages, which we address in the next subsection, is entirely absent from this dimension. This scarcity suggests that the field has prioritized the prediction of strength from intrinsic mixture properties over the equally important extrinsic environmental history. We consider this a significant limitation for real-world deployment, where concrete is rarely cast or cured under ideal laboratory conditions.

Another observation from Table 7 is the diversity of prediction targets across the three studies. While [59] and [60] both target residual strength after thermal attack, they do so for different material bases (nano concrete versus waste powder concrete), which prevents a direct comparison of model performance. [71] targets a broader but less extreme range of curing conditions, making it more relevant to standard construction practice but less directly comparable to the fire studies. This heterogeneity within a small sample size underscores the need for future research that systematically varies both the environmental condition and the concrete type within a single, unified modeling framework. Such a framework could potentially uncover universal patterns in how temperature history and moisture availability affect the predictive power of machine learning algorithms.

F. Early Age and Real-Time Strength Prediction: From Hydration Monitoring to Model-Driven Design

The ability to predict the compressive strength of concrete at very early ages, typically within the first 24 to 72 hours after casting, represents a critical capability for modern construction practice. Early-age strength data inform crucial decisions regarding formwork removal, post-tensioning schedules, and construction sequencing, all of which have direct economic and safety implications. Traditional testing protocols, such as the standard 28-day compressive test, are inherently retrospective and cannot provide the immediate feedback needed for dynamic construction management. The machine learning literature has therefore begun to address this gap, developing both static models that predict strength as a function of age and real-time frameworks that continuously assimilate hydration monitoring data. Our analysis of the corpus identified four studies that specifically target this early-age prediction dimension, each offering a distinct methodological perspective.

The most direct approach to this problem is the development of models that include concrete age as an explicit input feature, allowing the prediction of strength at any arbitrary time point. This strategy is adopted by [23], which investigated the compressive strength of fly ash concrete across multiple ages. The authors developed a novel machine learning method that incorporated the age of the samples, along with their ingredients including cement, fly ash, aggregates, and water, as input parameters. By treating age as a continuous variable, the model could generate a strength-versus-age curve, effectively capturing the time-dependent pozzolanic reaction of fly ash. We find that this study is particularly valuable because it bridges the gap between the conventional 28-day prediction paradigm and the practical need for strength estimates at earlier ages, such as 3, 7, and 14 days. The model was able to learn the nonlinear acceleration of strength gain that occurs as fly ash particles increasingly react with the calcium hydroxide produced by cement hydration, a phenomenon that is difficult to capture with simple empirical formulas.

The integration of supplementary cementitious materials (SCMs) with age-based prediction is further refined by [72], which presented a novel approach to predicting the early-age compressive strength of concrete by explicitly incorporating eco-friendly design considerations. This study is notable because it aligns the goal of predictive accuracy with the broader objective of sustainable concrete production. The authors argued that AI-driven modeling serves as a robust tool for designing eco-friendly concrete that must simultaneously satisfy strength requirements and reduce cement consumption. We view this work as an important conceptual bridge between performance prediction and material optimization, suggesting that early-age strength models are not merely passive forecasting tools but can actively guide the mix design process to minimize environmental impact.

A qualitatively different approach to early-age prediction is the use of continuous hydration monitoring to enable real-time prediction. This is the central contribution of [73], which proposed a framework for the real-time prediction of early concrete compressive strength using a combination of artificial intelligence and hydration monitoring. Instead of relying solely on static mixture parameters, this study continuously measured the temperature evolution of the hydrating cement paste, which serves as a proxy for the rate and extent of the hydration reaction. The AI models then assimilated this real-time temperature data to update the strength prediction dynamically as the concrete aged. We consider this a significant methodological advancement because it moves beyond the static, batch-processing paradigm of most ML applications and enters the domain of online, adaptive prediction. The ability to integrate sensor data in real time means that the model can account for the actual curing conditions experienced by each specific batch of concrete, which are often different from the idealized laboratory conditions under which static models are trained. This study essentially creates a digital twin of the hydration process, where the model learns the relationship between the instantaneous hydration state and the resulting strength.

The fourth study in this dimension, [18], focused on a specialized material class: ultra-high-performance fiber-reinforced concrete (UHPFRC). While all three previous studies addressed early-age strength prediction, [18] is unique in its material specificity and its emphasis on the optimization of the mixture itself. The study investigated AI-driven prediction of early-age compressive strength in UHPFRC, and through error analysis, the authors examined differences in prediction accuracy between various machine learning algorithms. The work highlighted the practical utility of machine learning in UHPFRC mix optimization, demonstrating that early-age strength prediction could be used to rapidly iterate through potential mixture compositions without the need for 28-day wait times. We note that this study is particularly relevant for precast and high-performance construction, where UHPFRC is used in elements that require early formwork removal or early prestress transfer.

Table 8. Summary of studies targeting early age and real-time compressive strength prediction.

Study ID	Prediction Paradigm	Material Type	Key Input Features	Prediction Target Age(s)	ML Algorithms Used	Unique Contribution
[23]	Static age-inclusive	Fly ash concrete	Cement, fly ash, age, aggregates, water	Multiple ages (e.g., 3, 7, 14, 28 days)	Novel machine learning method	Captured pozzolanic strength development over time using age as a feature
[72]	Static age-inclusive	Eco-friendly concrete	Mix design parameters, age	Early ages (within first 28 days)	AI-driven modeling	Integrated eco-design constraints with early-age strength prediction

Study ID	Prediction Paradigm	Material Type	Key Input Features	Prediction Target Age(s)	ML Algorithms Used	Unique Contribution
[73]	Real-time dynamic	General concrete	Hydration temperature monitoring data	Real-time (continuously updated)	AI models	Introduced real-time hydration monitoring as input for adaptive prediction
[18]	Static early-age	UHPFRC	Fiber content, mix proportions, age	Early ages (within days)	Various AI algorithms	Focused on specialized ultra-high-performance material with optimization orientation

As synthesized in Table 8, the four studies in this dimension can be categorized along two methodological axes: *static* versus *real-time* prediction, and *general* versus *specialized* concrete. [23] and [72] both belong to the static category, where the model is trained on a dataset that includes age as a feature, and it then generates predictions for any requested age without the need for any real-time input. This approach is computationally efficient and straightforward to implement, but it cannot adapt to batch-to-batch variability in curing conditions. In contrast, [73] breaks new ground by introducing the real-time paradigm, which is inherently more robust to environmental variability but requires the installation of continuous monitoring sensors. The fourth study, [18], occupies a hybrid position in this space; it is static in its input structure but specialized in its material focus, and it explicitly uses the prediction capability for optimization rather than for monitoring.

The diversity of concrete types represented in these four studies is noteworthy. Research on fly ash concrete [23] addresses the challenge of predicting strength when one of the cementitious components exhibits delayed reactivity, a feature that complicates early-age prediction because the strength gain trajectory is non-uniform. The eco-friendly concrete study [72] extends this logic to any concrete mixture that uses reduced cement content, which is the essence of sustainable concrete design. The real-time hydration monitoring work [73] is agnostic to the specific concrete type, suggesting that the methodology could be applied broadly, though the specific temperature-response patterns would need to be learned for each new mixture family. Finally, the UHPFRC study [18] demonstrates that early-age prediction is not limited to ordinary concretes but is also highly relevant for high-performance systems where early strength is a critical design parameter.

A common thread running through all four studies is the reliance on regression-based supervised learning, though the specific algorithms vary. [23] developed a novel machine learning method that was tailored to the fly ash concrete dataset, while [72] employed a more general AI-driven modeling approach without specifying a single algorithm as superior. [73] used AI models that were specifically adapted for time-series data (the hydration temperature curve), and [18] evaluated multiple AI algorithms to identify the one that minimized prediction error for UHPFRC. This heterogeneity in algorithm choice, even within the small early-age subset, underscores a broader theme of our review: there is still no universally accepted "best" algorithm for any given concrete prediction task. Instead, the optimal choice depends on the nature of the input data, the specific concrete material, and the prediction paradigm (static vs. real-time).

Another important aspect of the early-age prediction studies is their approach to validation. [23] and [72] both validated their models using experimental datasets that included test results at multiple ages, which is the standard approach for static models. [73] required a more elaborate validation framework because the model makes predictions in real time; the model's accuracy had to be evaluated over a time series of predictions, comparing the predicted strength trajectory against the actual measured strengths at specific test points. [18] used a conventional train-test split on their UHPFRC dataset but specifically focused on the early-age subset of the data. The differences in validation strategies across these studies reflect the fundamental differences in the prediction problem itself, and they highlight the need for standardized evaluation protocols for real-time prediction frameworks.

The practical implications of the early-age prediction capabilities described in these four studies are substantial. If a construction team can obtain reliable strength predictions within hours of casting, rather than waiting days or weeks, they can optimize their construction schedule, reduce the risk of premature formwork removal, and minimize the time and cost associated with quality control testing. The real-time framework proposed by [73] is particularly promising because it can provide continuous updates as the concrete cures, allowing managers to make informed decisions about when to proceed with subsequent construction activities. The static models from [23] and [72] are easier to deploy because they require no real-time data input, yet still offer the advantage of predicting strength at any arbitrary age, thereby reducing the need for multiple time-consuming physical tests. The UHPFRC-focused study [18] further demonstrates that these predictive capabilities are not limited to conventional concrete but extend to the most advanced and high-performance cementitious systems.

Despite these clear advancements, we identify several limitations in the current state of early-age and real-time strength prediction. First, the number of studies is extremely small, with only four studies in our corpus of 94 addressing this dimension. This scarcity suggests that the research community has only recently begun to appreciate the importance of early-age prediction, and that much more work is needed to develop robust, validated models for a wider range of concrete types. Second, the real-time prediction paradigm represented by [73] requires a significant investment in sensor technology and data infrastructure, which may be a barrier to adoption in many construction settings. Future research should explore whether simpler proxy variables, such as ambient temperature or maturity indices, can substitute for direct hydration temperature monitoring. Third, none of the four studies explicitly evaluated the generalization capability of their models to concrete mixtures that were not represented in the training data. The datasets used in [23], [72], and [73] each covered a relatively narrow range of mix designs, and the UHPFRC study [18] was limited to a single material class. This lack of cross-material validation leaves open the question of whether these early-age models can be reliably transferred to new concrete types or even to the same concrete cast under different environmental conditions.

G. Optimization Techniques and Metaheuristics: Tuning Algorithms for Superior Strength Prediction

The performance of machine learning models for concrete compressive strength prediction is highly sensitive to their hyperparameters, which control model complexity, learning dynamics, and regularization. Manual tuning of these parameters is often impractical due to the high dimensionality of the search space, prompting a growing body of research to adopt automated optimization techniques and metaheuristic algorithms. Our analysis of the included studies reveals a substantial and methodologically diverse engagement with optimization, spanning from classical grid search and Bayesian optimization to sophisticated evolutionary algorithms and swarm intelligence methods. This dimension is critical because the choice of optimization strategy can be as influential as the choice of the base algorithm itself in determining final prediction accuracy.

The optimization landscape can be categorized into two broad paradigms: deterministic hyperparameter optimization methods, which systematically evaluate a predefined search space, and stochastic metaheuristic methods, which utilize population-based or nature-inspired heuristics to navigate complex, multimodal error surfaces. The deterministic approach is primarily represented by Bayesian optimization and grid search, while the metaheuristic family includes genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization, grey wolf optimization, and forensic-based investigation, among others. To systematically map this diversity, we present a comprehensive taxonomy of the optimization techniques employed across the included studies, along with the specific machine learning algorithms they were used to tune.

Table 9. Taxonomy of optimization techniques and metaheuristics used for tuning machine learning models in concrete compressive strength prediction.

Optimization Category	Specific Optimization Technique	Tuned Machine Learning Algorithm	Concrete Material	Sources
Bayesian Optimization	Bayesian Optimization	Hybrid Bagging-NN, Stacking, RF, GPR	Recycled Aggregate Concrete (RAC)	[42]
	Bayesian Optimization	Advanced ML models	General Blended Concrete with XAI	[63]
	Bayesian Optimization	Hybrid models (e.g., RF with BO)	Blended Concrete (with POFA)	[37]
	Bayesian Optimization	Ensemble models	Palm Oil Fuel Ash Concrete	[38]
	Bayesian Optimization	Gradient Boosting	General Concrete	[74]
Genetic Algorithm (GA)	GA	Artificial Neural Network (ANN)	High-Strength Concrete (HSC)	[75]
	GA	Machine Learning Models	Fly Ash Concrete	[76]
	GA	Machine Learning Models	General Concrete (with AI)	[77]
	GA	Advanced ML models	General Blended Concrete	[63]
Particle Swarm Optimization (PSO)	PSO	Machine Learning Models	Fly Ash Concrete	[76]
	PSO	ANN, ANFIS	Fiber-Reinforced Concrete (with SiO2)	[31]
	PSO	ML models	General Concrete	[74]

Optimization Category	Specific Optimization Technique	Tuned Machine Learning Algorithm	Concrete Material	Sources
			(optimization)	
Grey Wolf Optimization (GWO)	GWO	ANN, ANFIS	Fiber-Reinforced Concrete (with SiO2)	[31]
Ant Colony Optimization (ACO)	ACO	XGBoost	General Concrete	[74]
Forensic-Based Investigation (FBI)	FBI	XGBoost	Ready-Mixed Concrete	[78]
Hybrid/General Evolutionary	General Evolutionary	Hybrid Models	Concrete (with POFA)	[37]

As Table 9 illustrates, the most widely adopted optimization technique across the corpus is **Bayesian optimization**, which appears in five distinct studies. [42] applied Bayesian optimization to tune bagging neural network, stacking, random forest, and Gaussian process regression models for predicting the compressive strength of recycled aggregate concrete (RAC). The study demonstrated that on RAC, Bayesian optimization led to substantial improvements in predictive accuracy over the manually-tuned counterparts, and it was particularly effective at identifying the optimal regularization strength and tree depth for the random forest model. We find that this work is significant because it not only applies optimization but also systematically compares the optimized models, revealing that the best-performing model configuration is highly dependent on the specific mixture composition, a nuance that manual tuning often misses. [63] integrated Bayesian optimization with a metaheuristic approach for blended concrete, using the technique to tune both the hyperparameters of XGBoost and the feature selection mask. The dual objective of optimizing both the model and its input space proved to be more powerful than either optimization alone.

The work by [37] extended the application of Bayesian optimization to hybrid machine learning models for predicting the compressive strength of palm oil fuel ash (POFA) concrete. The hybrid models were constructed by combining multiple base learners, and Bayesian optimization was used to determine the optimal weights for the ensemble. The study reported that the optimized hybrid model significantly outperformed the individual base models, underscoring the synergistic benefit of combining multiple predictors with automated tuning. [38] continued this line of inquiry by using Bayesian optimization to tune ensemble models for the same POFA concrete dataset, but with the additional refinement of using SHAP analysis to interpret the optimized model's predictions. This integration of optimization and explainability within a single framework is a methodological advancement that we consider to be a best practice for future research, as it ensures that the pursuit of higher accuracy does not come at the cost of model transparency. [74] conducted a comparison study of multiple optimization techniques, including Bayesian optimization, and found that while Bayesian optimization was computationally efficient for small to medium hyperparameter spaces, it struggled in high-dimensional settings, where stochastic metaheuristics proved to be more robust.

The second most prevalent optimization category is the **genetic algorithm (GA)** . [75] used a GA to optimize an artificial neural network (ANN) for predicting the compressive strength of high-strength concrete. The GA was employed to evolve the number of hidden layers, the number of neurons per layer, and the learning rate, thereby automating a task that would otherwise require extensive trial-and-error experimentation. The study reported that the GA-optimized ANN achieved a mean absolute error that was 18% lower than that of a manually tuned ANN, a substantial improvement that underscores the value of automated optimization for complex network architectures. [76] extended the use of GA to optimize a broader set of machine learning models for fly ash concrete, including neural networks and support vector machines. The GA was configured to simultaneously optimize multiple hyperparameters for each model class, and the results showed that the optimized models consistently outperformed their default configurations, but that the performance gains were model-dependent. We observe that this study is particularly insightful because it reveals that not all models benefit equally from optimization; some algorithms, such as random forest, are relatively robust to hyperparameter changes, while others, such as ANNs, are highly sensitive.

[77] adopted a GA to optimize a suite of AI-based models for general concrete, with a focus on improving both prediction accuracy and generalization. The study introduced a novel fitness function that combined a weighted sum of the root mean squared error (RMSE) on the training set and the RMSE on a validation set, thereby explicitly penalizing overfitting during the optimization process. This is a critical methodological detail because conventional GA implementations that only optimize training accuracy often produce models that fail to generalize to unseen data. We consider this study's approach to be a best practice that should be more widely adopted in the field. [63], in addition to using Bayesian optimization, also explored GA as an alternative metaheuristic, and the comparison revealed that GA was more computationally expensive than Bayesian optimization but often found better solutions when the hyperparameter space was large and multimodal. This trade-off between computational cost and solution quality is a recurring theme across the optimization literature.

Particle swarm optimization (PSO) is the third most represented technique. [76] compared PSO with GA for optimizing models for fly ash concrete and found that while both metaheuristics converged to similar final solutions, PSO converged more rapidly, requiring fewer function evaluations. This efficiency advantage is a well-known property of PSO, and it makes the technique particularly attractive for large-scale optimization problems where the base model is computationally expensive to evaluate, such as deep neural networks. [31] employed PSO to tune both ANNs and adaptive neuro-fuzzy inference systems (ANFIS) for fiber-reinforced concrete containing silica (SiO2). The study specifically compared PSO with grey wolf optimization (GWO), another recent swarm intelligence algorithm, and reported that PSO yielded slightly better average accuracy but GWO exhibited lower variance across multiple optimization runs. This finding suggests that GWO may be more robust to the stochasticity inherent in swarm-based optimization, making it a safer choice for applications requiring high reliability. [74] also included PSO in their comparison of optimization techniques and confirmed its efficiency, but noted that PSO could get trapped in local optima for problems with highly rugged error surfaces, a limitation that was partially mitigated by hybridizing PSO with local search operators.

Grey wolf optimization (GWO) , as mentioned, was used by [31] and is a relatively newer addition to the field, inspired by the social hierarchy and hunting behavior of grey wolves. In that study, GWO was applied to optimize the same ANNs and ANFIS models as PSO, and the results showed that GWO achieved slightly lower average RMSE than PSO but with a narrower confidence interval, indicating greater consistency across runs. We interpret this as evidence that GWO is a promising alternative to the more established PSO for hyperparameter tuning in concrete strength prediction, and we recommend that future comparative studies include GWO alongside GA and PSO. **Ant colony optimization**

(ACO) was employed by [74] to optimize an XGBoost model, and the study found that ACO was particularly effective at selecting the optimal number of boosting rounds and the learning rate, which are discrete hyperparameters that are difficult to optimize with gradient-based methods. The study noted that ACO required a carefully tuned pheromone decay rate to avoid premature convergence, a parameter that itself required optimization.

A unique and particularly innovative optimization approach is the **forensic-based investigation (FBI)** method used by [78]. The FBI algorithm is a relatively novel metaheuristic that simulates the process of criminal investigation, including suspect identification and evidence collection, to navigate the search space. [78] applied the FBI algorithm to optimize an XGBoost system for predicting the compressive strength of ready-mixed concrete. The FBI-optimized XGBoost achieved a coefficient of determination (R^2) greater than 0.98 and significantly outperformed both baseline and manually tuned XGBoost models. The study argued that the FBI algorithm is particularly well-suited to this problem because it balances exploration and exploitation more effectively than classical GA or PSO, a claim supported by the empirical results. We view this work as a pioneering application of a non-conventional metaheuristic to concrete strength prediction, and it suggests that the field can benefit from exploring the rich trove of novel optimization algorithms emerging from the broader computational intelligence community.

Finally, we note the study by [37], which applied a hybrid evolutionary algorithm approach. In that work, the authors did not use a single standard metaheuristic but rather developed a custom hybrid optimizer that combined elements of GA with Bayesian optimization to tune the hybrid ML models for POFA concrete. The hybrid approach was designed to leverage the Bayesian optimizer's efficiency in small local neighborhoods while using the GA's population-based search to escape local minima. The resulting optimized model achieved the highest accuracy among all tested configurations, suggesting that hybrid optimization strategies may offer the best of both worlds.

Across all the optimization studies, several important cross-cutting observations emerge. First, we find that optimization is not a one-size-fits-all solution; the effectiveness of a given technique depends on the algorithm being tuned, the size and quality of the dataset, and the dimensionality of the hyperparameter space. For simple models with few hyperparameters, such as shallow neural networks, Bayesian optimization is often sufficient. For complex models like deep networks or ensembles, population-based metaheuristics such as GA, PSO, or GWO are generally more effective but at a higher computational cost. Second, none of the studies in our corpus performed a direct, systematic, and controlled comparison of all major optimization algorithms on the same dataset and the same base model. This absence makes it difficult to draw definitive conclusions about which technique is universally best. [74] came the closest to such a comparison but limited its scope to only three techniques (Bayesian, PSO, ACO). We therefore recommend that future research include comprehensive benchmark studies that compare Bayesian optimization, GA, PSO, GWO, ACO, and FBI on a common repository of concrete strength data. Third, we observe that most optimization studies focus exclusively on maximizing predictive accuracy, with no consideration of secondary objectives such as model complexity or inference time. In a practical deployment scenario, a model that is 90% as accurate but ten times faster to train or to evaluate may be preferable. This multi-objective optimization perspective is entirely absent from the current literature and represents a promising direction for future work.

IV. DISCUSSION

Synthesizing the key findings across the eight thematic dimensions of this review reveals a field that has matured rapidly from a proof-of-concept phase into a sophisticated methodological landscape, yet one characterized by notable asymmetries in depth and coverage. Taken together, the results demonstrate that machine learning models, particularly ensemble tree methods and deep neural networks, consistently achieve high predictive accuracy for concrete compressive strength across a wide variety of material types. The evidence emerges across studies with remarkable consistency: gradient boosting machines and random forests, when coupled with careful feature engineering and hyperparameter optimization, frequently reported coefficient of determination values exceeding 0.95, and in some cases approaching 0.99, for diverse datasets spanning ordinary Portland cement concrete to ultra-high-performance fiber-reinforced composites. This pattern of consistently high performance across different experimental conditions and concrete families suggests that the fundamental modeling capability of these algorithms is robust and generalizable beyond the specific datasets on which they were trained. However, our synthesis also uncovered a significant contradiction: the very algorithms that achieve the highest predictive accuracy, such as deep neural networks and complex ensemble models, are also the ones that are most opaque and least amenable to interpretation. This tension between accuracy and transparency, which we have traced across multiple dimensions of the literature, represents the central methodological challenge facing this research domain.

The implications of this synthesis for both theoretical understanding and practical application are substantial. From a theoretical perspective, our findings suggest that the relationship between concrete composition and compressive strength, long recognized as nonlinear and multivariate, can be captured with high fidelity by data-driven models that do not rely on explicit physical laws. This is not to say that machine learning models have rendered domain knowledge obsolete; rather, the most successful studies in our corpus were those that informed feature selection and model design with sound cement chemistry principles. For example, studies that included carefully derived interaction terms, such as the water-to-binder ratio normalized by the reactivity of supplementary cementitious materials, consistently outperformed those that merely fed raw mix proportions into a generic model. We interpret this as evidence that the optimal modeling strategy is a hybrid one, where domain expertise guides the feature engineering process while machine learning handles the complex residual nonlinearities that physics-based models cannot capture. This conclusion has direct theoretical implications for how we conceptualize the relationship between material composition and mechanical properties: it is neither purely deterministic nor purely stochastic, but rather a combination of known physicochemical trends and unexplained variance that machine learning can absorb.

The practical implications of our review are equally far-reaching. For civil engineers and construction practitioners, the evidence strongly indicates that machine learning models, particularly those optimized using metaheuristic algorithms, can serve as reliable proxies for physical compression testing, especially in scenarios where traditional testing is impractical due to time, cost, or material constraints. The ability to predict strength at very early ages using hydration monitoring data, as demonstrated by one study in our corpus, opens the door to real-time construction management decisions that could significantly accelerate project timelines and reduce waste. Moreover, the integration of non-destructive testing data, such as ultrasonic pulse velocity measurements, into machine learning frameworks offers a pathway to in-situ strength assessment without the need for destructive core sampling. For policymakers and standards organizations, our review suggests that the time is ripe for developing codified guidelines for the use of AI-based strength prediction in quality control and mix design optimization. However, we caution that such guidelines must mandate the inclusion of explainability assessments, since our analysis reveals that the overwhelming majority of studies still do not provide any form of model interpretation. Without this transparency, regulatory acceptance will remain elusive, as engineers cannot be expected to trust predictions whose underlying rationale is opaque.

Acknowledging the limitations of this review is essential for contextualizing its conclusions. The most significant methodological constraint concerns the scope of the database search and the inclusion criteria. While we queried five major databases and applied a rigorous PRISMA-based screening process, it is possible that relevant studies published in non-indexed journals, conference proceedings from regional engineering societies, or in languages other than English were inadvertently excluded. This language bias is a well-recognized limitation of systematic reviews in engineering disciplines, and it may skew our findings toward research originating from English-speaking countries and institutions with access to high-impact international journals. A second limitation relates to the quality assessment of the included studies. Because our review prioritized breadth of coverage across eight thematic dimensions, we did not perform a formal risk-of-bias assessment or a critical appraisal of each study's experimental design. This means that we must treat the reported performance metrics with some caution, as studies with small datasets, inadequate validation procedures, or overly optimistic train-test splits may report inflated accuracy figures. The potential for publication bias is also present, as studies that report negative results or poor model performance are less likely to be published in peer-reviewed venues, and our exclusion of grey literature and theses further compounds this risk. Consequently, the cumulative performance landscape we have mapped may be more optimistic than the true state of the art. Finally, the subjectivity inherent in thematic analysis, despite our use of a predefined analytical framework, means that a different set of reviewers might have emphasized different patterns or drawn slightly different conclusions from the same corpus.

These limitations, however, do not negate the value of our synthesis; rather, they illuminate specific directions for future research. One critical area that remains understudied is the development of standardized, publicly available benchmark datasets for concrete compressive strength prediction. As our review has shown, the field is characterized by a proliferation of bespoke experimental datasets, each with different features, sample sizes, and concrete types. This fragmentation makes it nearly impossible to perform a fair and rigorous comparison of different machine learning algorithms under controlled conditions. Future research should therefore prioritize the creation of a comprehensive, open-access repository that aggregates experimental data from multiple laboratories, spanning a wide range of concrete compositions, curing conditions, and testing ages. Such a repository would not only enable more reliable algorithm benchmarking but would also facilitate the development of models that can generalize across the diverse material types we have documented. There is a pressing need for collaborative efforts among research groups to harmonize data collection and reporting standards, a task that would benefit from the involvement of professional engineering societies and international standards organizations.

Another important avenue for future work involves the systematic integration of explainable AI into the modeling pipeline. Our review found that more than 85% of the studies did not employ any interpretability technique, and among those that did, SHAP analysis was the overwhelming method of choice. While SHAP is a powerful and theoretically grounded approach, it is not without limitations, particularly its computational cost for models with a large number of features or deep tree ensembles. Future research should explore alternative or complementary interpretability methods, such as partial dependence plots, accumulated local effects, or counterfactual explanations, and should compare their utility and fidelity for concrete strength prediction specifically. Moreover, researchers should move beyond post-hoc explanations and begin to develop inherently interpretable models, such as generalized additive models or rule-based learners, that can achieve competitive accuracy while remaining transparent by design. Our findings also point to a need for longitudinal studies that track the performance of machine learning models over time as new experimental data become available. Most of the reviewed studies are static, training and evaluating models on a fixed dataset. In practice, a predictive model deployed in a concrete plant would need to adapt to seasonal variations in raw materials, changes in supplier specifications, and shifts in production processes. Research on online learning, active learning, and model updating strategies is almost entirely absent from the corpus and represents a critical gap for real-world deployment.

The intersection of metaheuristic optimization and model interpretability is another area ripe for exploration. While we documented a rich diversity of optimization techniques, from genetic algorithms to forensic-based investigation, none of the reviewed studies explicitly considered how the optimization process influences the interpretability of the resulting model. It is plausible, for instance, that a model tuned by a highly aggressive optimizer to achieve peak accuracy on a training set may rely on spurious correlations that are not robust to new data or that are difficult to explain. Future research should explore multi-objective optimization frameworks that simultaneously maximize predictive accuracy and minimize model complexity or maximize global interpretability metrics. Such frameworks would produce models that are not only accurate but also transparent and trustworthy, directly addressing the accuracy-interpretability tension we identified. Additionally, the optimization techniques themselves could be used to automate the selection of XAI methods, tailoring the interpretability approach to the specific architecture and dataset at hand.

Finally, we highlight the need for research that bridges the gap between laboratory-scale prediction models and field-scale application. The vast majority of studies in our corpus used data collected under controlled laboratory conditions, with carefully measured mix proportions and standardized curing regimes. In real construction environments, however, concrete is subject to uncontrolled variability in aggregate moisture content, ambient temperature, and workmanship quality. Future research should therefore focus on developing and validating machine learning models using data collected from actual construction sites, including truck-mounted sensors, batching plant logs, and field-cured test specimens. The incorporation of such noisy, real-world data would test the robustness of current algorithms and likely reveal new challenges that are not apparent in pristine laboratory datasets. Moreover, models trained on field data would be directly applicable to the decision-making contexts faced by construction managers, such as when to remove formwork or when to apply post-tensioning forces. The early-age and real-time prediction studies we reviewed provide a promising starting point for this transition, but much more work is needed to scale these approaches from proof-of-concept to routine industrial practice. The integration of internet-of-things (IoT) sensor networks with cloud-based machine learning inference engines offers a technological pathway for such deployment, and we anticipate that research in this direction will accelerate significantly in the coming years.

V. CONCLUSION

This systematic literature review has synthesized ninety-four studies to map the landscape of artificial intelligence and machine learning models for predicting concrete compressive strength across eight thematic dimensions. The core insight that emerges from our analysis is that ensemble tree methods and deep neural networks, particularly when optimized via metaheuristic algorithms and informed by domain-specific feature engineering, consistently achieve high predictive accuracy across a wide spectrum of concrete types. We have confirmed that the field has matured beyond simple proof-of-concept demonstrations into a sophisticated methodological domain where hybrid models integrating experimental data, environmental factors, and optimization techniques can approach near-perfect prediction in controlled settings. However, our synthesis has also revealed a critical asymmetry: the very models that deliver the highest accuracy are those that remain most opaque, with more than eighty-five percent of the reviewed studies omitting any form of interpretability assessment. This finding challenges the prevailing assumption that accuracy alone is sufficient for practical deployment.

The practical and theoretical implications of our review are therefore intertwined. The evidence we have assembled underscores that machine learning can serve as a powerful tool for mix design optimization, early-age strength assessment, and sustainable concrete formulation, but only if model transparency and data diversity are prioritized alongside predictive performance. The substantial gaps we documented, particularly in the systematic integration of curing conditions, non-destructive testing fusion, and real-time monitoring, indicate that the current corpus leans heavily toward laboratory-controlled scenarios that may not generalize to field conditions. Future research must therefore pursue three complementary directions: the creation of standardized, open-access benchmark datasets spanning diverse concrete families and environmental exposures; the development of inherently interpretable models or the mandatory integration of explainability frameworks into all predictive pipelines; and the validation of laboratory-derived models against real-world construction data that capture uncontrolled variability. By addressing these gaps, the field can transition from academic precision toward industrially robust, transparent, and trustworthy prediction systems that meaningfully advance concrete technology and construction practice.

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His current PhD research and this review paper reflect his deep commitment to developing AI-driven predictive models for sustainable concrete, aiming to transform laboratory findings into reliable, real-world structural solutions.

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