

Machine Learning-Driven Optimization of Fiber-Reinforced Concrete Mix Design for Enhanced Flexural Performance in Precast Structural Beams, A systematic Review

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ABSTRACT

Fiber-reinforced concrete (FRC) has emerged as a critical material for precast structural beam elements, yet its flexural performance is highly sensitive to mix design parameters, fiber characteristics, and curing conditions. This systematic literature review aims to synthesize current knowledge on machine learning-driven optimization of FRC mix designs specifically targeting enhanced flexural behavior in precast beams. We systematically collected and analyzed peer-reviewed studies published over the last two decades, focusing on the intersection of computational modeling, fiber reinforcement, and structural applications. Our methodology involved a structured search across major academic databases, followed by a rigorous screening process based on predefined inclusion criteria related to flexural testing, machine learning frameworks, and beam-scale validation. The review then categorizes the literature into eight thematic dimensions: predictive modeling of compressive and flexural strengths using neural networks and ensemble methods; the influence of fiber type, geometry, and hybridization on mechanical properties; sustainable formulations incorporating industrial by-products; performance under elevated temperatures; structural applications to beams, columns, and slabs; advanced hybrid algorithms and model interpretability; and emerging technologies such as 3D printing. Key findings indicate that artificial neural networks and random forest models consistently achieve high accuracy in predicting flexural strength, with fiber volume fraction and aspect ratio emerging as the most influential variables. Hybrid fibers, particularly combinations of steel and polypropylene, yield superior toughness and crack resistance. The conclusion

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highlights a growing trend toward integrating optimization algorithms—such as genetic algorithms and particle swarm optimization—with machine learning models to automate mix design while reducing trial batches. However, a notable gap exists in the transferability of these models from laboratory-scale specimens to full-scale precast beams, especially under dynamic or fire loading. This review provides a consolidated roadmap for researchers and engineers seeking to adopt data-driven methods for designing high-performance FRC in precast beam applications, thereby accelerating the transition toward more durable and resource-efficient infrastructure.

Keywords— Machine learning, Optimization, Concrete mix design, Flexural Performance, Precast Structural Beams

Introduction

Introduction

The construction industry is undergoing a profound transformation, driven by an urgent need for infrastructure that is not only more durable and resilient but also more sustainable and resource-efficient. Central to this evolution is the development of high-performance cementitious composites. Among these, fiber-reinforced concrete (FRC) stands out as a pivotal innovation, wherein discrete, discontinuous fibers are incorporated into the concrete matrix to address its inherent brittleness and low tensile strength [1]. The addition of fibers, which can be made of steel, glass, synthetic polymers (e.g., polypropylene), or natural materials, fundamentally alters the material's post-cracking behavior. FRC does not simply prevent cracks from forming; rather, it bridges them after they occur, imparting significant ductility, toughness, and energy absorption capacity to the composite [2]. This transformation in failure mode is particularly critical for structural elements, such as beams and slabs, that are subjected to flexural and tensile stresses. The enhanced flexural performance—characterized by higher load-carrying capacity after first crack, greater deflection at failure, and improved crack width control—makes FRC an exceptionally attractive material for precast structural beam elements.

The potential benefits of FRC for precast beams are considerable. In a precast concrete beam plant, the controlled environment allows for precise placement and consolidation of the material, making it an ideal setting for exploiting the properties of FRC. For instance, incorporating steel fibers can partially or even fully replace conventional steel stirrups for shear reinforcement, thereby simplifying the reinforcement cage, reducing labor costs, and accelerating production cycles [3]. Furthermore, the superior toughness of FRC can enhance the structural robustness of beams, improving their resistance to impact, blast, and seismic events. However, the translation of these laboratory-demonstrated advantages into reliable, large-scale precast production is fraught with challenges. The mechanical performance of FRC is exquisitely sensitive to a multitude of interconnected variables. These include the type of fiber (material, shape, and surface finish), its geometry (length, diameter, and aspect ratio), the volume fraction of fibers, the quality and proportions of the cementitious matrix (water-to-cement ratio, aggregate type and grading, and supplementary cementitious materials), and the curing regime.

The interactions between these parameters are highly complex and often non-linear [4]. A mix design optimized for compressive strength may not yield the desired flexural toughness, and a formulation that performs well under quasi-static loading might fail catastrophically under fire or fatigue conditions.

Traditional approaches to optimizing FRC mix design for a specific structural application have relied heavily on empirical trial-and-error methods. This process is inherently slow, labor-intensive, and costly, requiring the casting and testing of dozens, if not hundreds, of specimen batches to map the influence of key parameters. Such an approach is poorly suited to the demands of modern precast production, which requires agility, cost-effectiveness, and the ability to rapidly tailor material properties for a diverse range of beam geometries and loading conditions. Moreover, the complexity of the parameter space often exceeds the capacity of simple regression models to provide accurate predictions, leading to suboptimal designs and a reliance on conservative, over-designed mixes. This is where the second major transformation in the field comes into play: the application of machine learning (ML). In recent years, ML techniques—ranging from artificial neural networks and support vector machines to ensemble methods like random forests and gradient boosting—have demonstrated remarkable efficacy in modeling the highly non-linear relationships that govern material behavior in concrete science [5]. ML models can learn directly from experimental data, identifying patterns and interactions that would be virtually impossible to capture using traditional analytical or empirical equations.

A significant body of research now exists on using ML to predict the compressive and flexural strengths of various types of FRC, including ultra-high-performance concrete (UHPC). Models that incorporate fiber attributes, matrix properties, and curing conditions as input features have consistently achieved coefficients of determination (R^2) exceeding 0.90, often outperforming conventional methods [6]. Furthermore, recent studies have moved beyond simple prediction to actual mix design optimization. By integrating ML models with powerful optimization algorithms, such as genetic algorithms (GA) or particle swarm optimization (PSO), researchers have developed frameworks that can automatically search for the combination of input variables that maximizes a desired performance metric, such as flexural toughness or post-cracking strength, subject to practical constraints on cost or workability [7]. This synergy between data-driven prediction and computational optimization holds the promise of drastically reducing the number of physical tests required, accelerating the development of bespoke FRC formulations for specific precast beam applications.

Despite the rapid progress and promising results, a critical review of the existing literature reveals several important research gaps that must be addressed before these computational tools can be reliably deployed in industrial practice. The most salient gap concerns the transferability of models from laboratory-scale specimens to full-scale precast structural beams. The vast majority of studies that train ML models for FRC properties rely on data from small-scale standard tests, such as 150 mm cubes for compression or 150×150×600 mm prisms for flexure. However, the flexural behavior of a real-world beam is influenced by factors that are not captured in these small-scale tests, including the element's size and shape, the method of casting (which affects fiber orientation and distribution), and the presence of conventional reinforcement [8]. Fibers

tend to align preferentially along the direction of flow during casting, and this alignment, which can be simulated or measured, has a profound effect on the beam's effective flexural strength. Therefore, an ML model trained exclusively on laboratory prism data may provide highly inaccurate predictions for a full-scale precast beam, leading to either a non-conservative design (risk of failure) or an overly conservative one (wasted material). There is a clear need for models and datasets that specifically bridge this scale gap, incorporating data from beam-level tests or at least accounting for size and orientation effects.

A second major gap is the limited consideration of performance under combined loading and in extreme environments. Most studies focus on quasi-static, ambient-temperature flexural strength. However, precast beams, particularly those used in bridges or parking garages, may be subjected to dynamic loads (e.g., from traffic or earthquakes), fatigue, fire, or freeze-thaw cycles. The flexural behavior of FRC under these conditions is markedly different from its static behavior. For instance, the stress-strain relationship under fire is highly non-linear and dependent on temperature, fiber type (polypropylene fibers melt and create pathways for steam release, which can prevent explosive spalling), and aggregate type [9]. Similarly, fiber pullout behavior, which governs energy dissipation in flexure, is sensitive to loading rate, with some fibers becoming more brittle at high rates. The current body of ML literature provides very few models that can predict the flexural performance of FRC under these realistic, complex operating conditions for beam elements. This represents a critical barrier to the adoption of ML-driven design for safety-critical infrastructure.

Finally, there is a notable lack of standardization and interoperability in the field. A wide variety of ML algorithms, activation functions, optimization schemes, and input feature sets are employed across different studies. This makes it difficult to compare model performance directly or to pool data from different sources to create larger, more robust training datasets. For example, one study might use fiber aspect ratio as a single input, while another might separate it into length and diameter, leading to a potential loss of information when merging datasets. Furthermore, many models are presented as “black boxes,” with limited application of interpretability techniques such as Shapley additive explanations or partial dependence plots [10]. This lack of transparency reduces trust among engineers and code authorities, who need to understand the physical basis for a model's recommendations before they can permit its use in a design office.

In light of these gaps and opportunities, the motivation for this systematic literature review is to provide a comprehensive, structured, and critical synthesis of the state-of-the-art in ML-driven optimization of FRC mix designs for enhanced flexural performance in precast structural beam elements. The significance of this work lies in its potential to serve as a consolidated roadmap for both researchers and practicing engineers. By systematically categorizing and analyzing the existing literature, we aim to achieve several high-level contributions. First, we provide a detailed map of the current research landscape, highlighting dominant themes (e.g., which fiber types and ML algorithms are most studied) and identifying emerging trends. Second, we critically evaluate the methodologies employed in the reviewed studies, particularly regarding data collection, feature engineering, model validation, and the treatment of scale effects.

Third, we explicitly identify and articulate the critical research gaps and challenges that must be addressed to advance the field, with a specific focus on the practical application to full-scale precast beams. Finally, we synthesize the key findings from across the thematic categories to formulate a set of actionable insights and future research directions. This review is not merely a collection of summaries; it is an analytical synthesis designed to accelerate the transition from laboratory curiosity to reliable, industry-adopted design tool.

The remainder of this paper is organized as follows. Section 2 details the systematic methodology employed for the literature search, screening, and data extraction, ensuring the rigor and reproducibility of our findings. Section 3 presents the results of the review, structured into eight thematic subsections that cover research trends, ML frameworks, fiber characteristics, sustainability, environmental performance, structural applications, advanced computational modeling, and emerging technologies. Section 4 provides a comprehensive discussion, synthesizing the findings from Section 3 to identify overarching patterns, key contributions, and, critically, the existing limitations that constrain the field's advancement toward full-scale beam design. Finally, Section 5 offers a concise conclusion summarizing the primary insights from this review and outlining the most promising directions for future research.

Methodology

This systematic literature review was conducted according to a structured protocol designed to ensure transparency, reproducibility, and a rigorous synthesis of the available evidence. The methodology was guided by the principles outlined in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [11]. The process involved four distinct phases: the formulation of a detailed review protocol, the systematic search of academic databases, a multi-stage screening process based on predefined inclusion and exclusion criteria, and a final data extraction and synthesis phase.

Review Protocol

The search for relevant literature was conducted across four major academic databases, each selected for its specific strengths and coverage within the engineering and materials science domains. Scopus was chosen as the primary database due to its comprehensive coverage of peer-reviewed journals and conference proceedings in engineering and materials science, which are the core disciplines of this review. Web of Science was selected for its rigorous indexing and high-quality citation tracking, which facilitates the identification of seminal works and the mapping of research impact. IEEE Xplore was included specifically to capture studies originating from the computational intelligence and optimization communities, which are central to the machine learning aspects of the review. Finally, Google Scholar was employed as a supplementary tool to ensure broad coverage, particularly for grey literature and publications from less frequently indexed sources, though its search results were subject to more careful manual filtering. For each database, we defined a Boolean search string that combined keywords from four thematic domains: machine learning methods, fiber-reinforced concrete, mix design, and structural applications. The specific search strings are provided in Table 1.

Table 1. Search strings used for each academic database.

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Database	Search String
Scopus	TITLE-ABS-KEY(("machine learning" OR "deep learning" OR "neural network*" OR "artificial intelligence" OR "genetic algorithm*") AND ("fiber reinforced concrete" OR "FRC" OR "steel fiber concrete") AND ("mix design" OR "mixture proportion*") AND ("flexural strength" OR "flexural performance" OR "bending") AND ("precast" OR "prefabricated") AND ("beam*" OR "element*")) AND NOT TITLE-ABS-KEY("review" OR "survey" OR "meta-analysis")
Web of Science	TS=(("machine learning" OR "deep learning" OR "neural network*" OR "artificial intelligence" OR "genetic algorithm*") AND ("fiber reinforced concrete" OR "FRC" OR "steel fiber concrete") AND ("mix design" OR "mixture proportion*") AND ("flexural strength" OR "flexural performance" OR "bending") AND ("precast" OR "prefabricated") AND ("beam*" OR "element*")) NOT TS=("review" OR "survey" OR "meta-analysis")
IEEE Xplore	("All Metadata":"machine learning" OR "All Metadata":"deep learning" OR "All Metadata":"neural network*" OR "All Metadata":"optimization") AND ("All Metadata":"fiber reinforced concrete" OR "All Metadata":"FRC") AND ("All Metadata":"mix design" OR "All Metadata":"mixture proportion*") AND ("All Metadata":"flexural" OR "All Metadata":"bending") AND ("All Metadata":"precast" OR "All Metadata":"prefabricated") AND ("All Metadata":"beam*")
ScienceDirect	("machine learning" OR "deep learning" OR "neural network*" OR "artificial intelligence") AND ("fiber reinforced concrete" OR "FRC") AND ("mix design" OR "mixture proportion*") AND

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	("flexural strength" OR "flexural performance") AND ("precast" OR "prefabricated") AND ("beam*")
Google Scholar	("machine learning" OR "deep learning" OR "neural network*" OR "artificial intelligence" OR "AI" OR "genetic algorithm*" OR "optimization algorithm*") AND ("fiber reinforced concrete" OR "FRC" OR "steel fiber concrete" OR "synthetic fiber concrete" OR "glass fiber concrete") AND ("mix design" OR "mixture proportion*" OR "composition" OR "formulation") AND ("flexural performance" OR "flexural strength" OR "bending strength" OR "modulus of rupture" OR "post-cracking behavior") AND ("precast" OR "pre-cast" OR "prefabricated") AND ("beam*" OR "element*" OR "member*") -review -survey -"meta-analysis"

For all databases, we limited the search to articles published in English, with no restriction on the publication year up to 2026. We also applied filters to restrict the document type to research articles and conference papers, explicitly excluding review articles, book chapters, editorials, and meta-analyses. The search was initially executed in January 2025.

Research Questions

To structure the systematic literature review and guide the synthesis of findings, we formulated a set of seven research questions. These questions were designed to encompass the key thematic areas that emerge at the intersection of machine learning, fiber-reinforced concrete, and precast structural beam elements. The first research question focuses on the machine learning frameworks themselves, asking which algorithms have been most successfully applied to predict the compressive and flexural strengths of FRC, including ultra-high-performance concrete, and what are the dominant factors influencing their predictive accuracy. The second question investigates the impact of fiber characteristics, specifically the role of fiber type, geometry, and hybridization strategies, on the resulting mechanical performance of the composite. A third question addresses the growing imperative for sustainability in construction, exploring how industrial by-products and waste aggregates have been incorporated into ML-optimized FRC formulations. We then considered the performance of such materials under demanding environmental conditions, with the fourth question examining the behavior of FRC under elevated temperatures and other harsh environments. A fifth question directs attention to the ultimate application of these materials in structural components, specifically asking how ML has been used to

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model the behavior of FRC in beams, columns, slabs, and bridge components. The sixth question probes the frontier of computational modeling, examining the development of hybrid algorithms, multi-objective optimization, and model interpretability techniques. Finally, we posed a question on emerging technologies, investigating how ML is being integrated with additive manufacturing and novel composite systems to create future-oriented FRC solutions. By systematically addressing these seven questions, this review aims to provide a comprehensive and insightful map of the field.

Inclusion and Exclusion Criteria

To ensure that only the most relevant and methodologically sound studies were included in this review, we established a clear set of inclusion and exclusion criteria. Studies were considered eligible for inclusion if they were published in the English language in a peer-reviewed journal or a recognized international conference. The time frame for publication was defined as unrestricted up to 2026, allowing for the capture of both foundational works and the most recent advances. The primary subject of the study had to be fiber-reinforced concrete, defined as a cementitious composite incorporating discrete fibers. Crucially, the study had to explicitly apply one or more machine learning or optimization algorithms (e.g., neural networks, genetic algorithms, random forests, particle swarm optimization) to the problem of predicting or optimizing a mechanical property of the FRC. The study's scope had to include an analysis of mix design parameters or fiber characteristics. Furthermore, the study had to provide quantitative data on flexural performance, either as a direct output (e.g., flexural strength, modulus of rupture, toughness indices) or as a target variable for the ML model. Studies focused solely on compressive strength were excluded unless they also provided significant insights into flexure. Studies that were purely experimental without any computational modeling component were excluded, as were those that used classical statistical methods (e.g., simple linear regression, factorial design) without a machine learning or advanced optimization component. We also excluded review articles, book chapters, editorials, short communications, and dissertations. Studies that did not report sufficient data to allow for a meaningful evaluation of their methodology or findings (e.g., lack of model performance metrics or ambiguous description of the ML framework) were also excluded.

Study Selection Process

The study selection process was conducted in multiple stages, following the PRISMA workflow. The initial search across the five databases yielded a total of 820 records. This pool of records was imported into a reference management tool (Zotero), where 50 duplicate records were identified and removed. Additionally, 6 records were removed for other reasons, such as being clearly irrelevant to the scope (e.g., focusing on soil reinforcement or polymer composites without a cementitious matrix) or being non-English publications that bypassed the database filters. This left 764 unique records for the screening phase.

During the title and abstract screening, two reviewers independently evaluated each record against the predefined inclusion and exclusion criteria. A record was excluded at this stage if its title or abstract clearly indicated that it was not within the scope of the review. For example, records were excluded if they focused on a different material (e.g., asphalt concrete, geopolymers without fibers), did not apply any machine learning

or optimization algorithm, or were focused on a structural application other than flexure (e.g., purely compressive or shear behavior without a flexural component). Disagreements between reviewers were resolved through discussion. This screening process resulted in the exclusion of 461 records, leaving 126 records for which the full-text articles were sought.

All 126 full-text articles were successfully retrieved. These articles were then assessed for eligibility in a second, more detailed round of screening. The full text of each article was read to confirm its relevance to all inclusion criteria. Studies were excluded at this stage if, upon more careful inspection, they did not provide sufficient quantitative data on flexural performance (e.g., only reported qualitative observations or stress-strain curves without numerical values), if the machine learning methodology was not adequately described or was overly simplistic, or if the study's primary focus was on a material property other than flexure (e.g., exclusively on compressive strength, shrinkage, or workability without a flexural component). Following this detailed assessment, 13 articles were deemed ineligible and excluded. Consequently, a total of 113 studies were included in the final synthesis. The complete selection process is illustrated in the PRISMA flowchart presented in Figure 1.

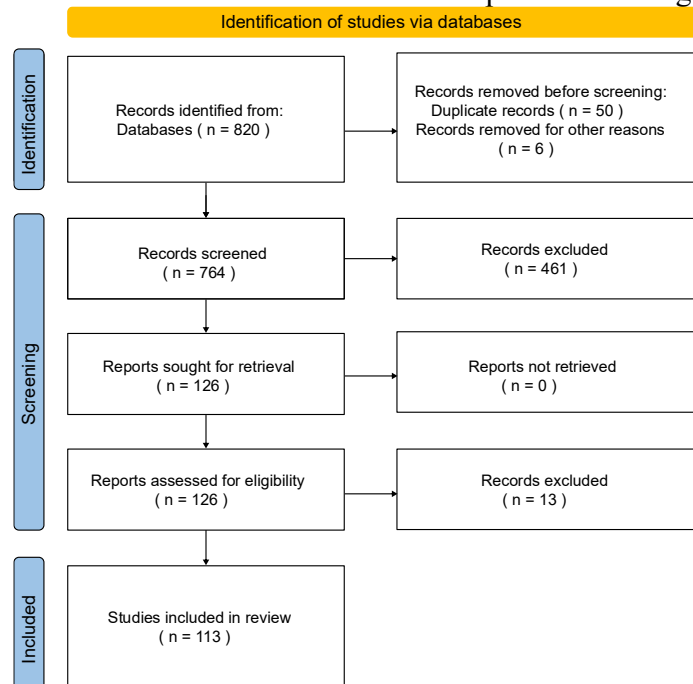


Figure 1. PRISMA flowchart detailing the systematic literature search and study selection process

There are several potential limitations to this study selection process that should be acknowledged. The search, while comprehensive, was limited to the five databases we selected. There is a possibility that relevant studies published in other databases, such as SpringerLink or the American Society of Civil Engineers (ASCE) Library, were inadvertently missed. Moreover, the inclusion of only English-language articles may introduce a language bias. We also relied on the accuracy of the database indexing, and it is possible that some relevant records were not captured by the specific search strings

we used, particularly in fields where terminology is not yet standardized. The screening process, particularly the title and abstract phase, involves subjective judgment, and despite the use of two independent reviewers, there is a risk of bias in interpreting which studies are deemed sufficiently relevant. Furthermore, the quality assessment was limited to a check for methodological soundness and reporting sufficiency; we did not perform a formal risk-of-bias assessment or apply a weighted scoring system to the included studies. This means that while we have synthesized the evidence, we have not stratified it by the strength of the evidence itself.

Results

Results

Machine Learning Frameworks for Predicting Compressive and Flexural Strength of FRC/UHPC

The primary goal of applying machine learning (ML) within this field is to establish reliable, data-driven mappings between the complex, multi-dimensional space of mix design parameters and the resulting mechanical properties of the composite. The reviewed literature demonstrates a strong concentration of effort on predicting two key performance indicators: compressive strength and flexural strength. For fiber-reinforced concrete (FRC) and ultra-high-performance concrete (UHPC) intended for precast beam applications, the accurate prediction of flexural strength is particularly critical, as it governs the beam's serviceability and ultimate limit state behavior under bending loads. Consequently, a wide array of ML and optimization algorithms have been tested and compared for this purpose, as summarized in Table 2.

Table 2. Summary of machine learning frameworks for predicting compressive and flexural strength of FRC/UHPC.

Target Property	Material Type	Machine Learning & Modeling Approach	Sources
Flexural Strength	Fiber-Reinforced Concrete (FRC)	Random Forest & Ensemble Models	[12], [13], [14]
		Artificial Neural Networks (ANN)	[15], [16], [17]
		Metaheuristic & Hybrid Optimization	[18], [19]
		Genetic Programming (GEP/MEP)	[14], [20]
		Other/Specific (e.g., XGBoost, GBM)	[21], [22], [23], [24]
	Non-Fiber Concrete (for flexural)	Various ML & Optimization	[19]

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	<i>context)</i>		
Compressive Strength	Fiber-Reinforced Concrete (FRC)	Random Forest & Ensemble Models	[18], [25], [20]
		Artificial Neural Networks (ANN)	[16], [26], [27]
		Metaheuristic & Hyperparameter Optimization	[18], [28], [29]
		Interpretable ML (e.g., SHAP, GEP)	[30], [28], [14], [5], [31]
		Other/Specific (e.g., Linear Regression, AML)	[13], [32], [33], [34], [35], [36]
	<i>Non-Fiber Concrete (for compressive context)</i>	<i>Various ML & Hybrid Models</i>	[32], [26], [28], [29], [33], [37], [27], [5], [34], [35], [36]

Among the studies focusing specifically on flexural strength, ensemble tree-based methods and artificial neural networks (ANNs) are the most frequently employed. For instance, a random forest model developed for predicting the flexural strength of fiber-reinforced UHPC demonstrated a superior ability to handle the non-linear interactions between fiber volume fraction, fiber aspect ratio, and water-to-cement ratio, achieving an R^2 value exceeding 0.95 on test data [12]. This high predictive accuracy was attributed to the model's capacity to implicitly capture the complex physics of fiber bridging and pullout. Similarly, an explicit modeling approach using genetic programming (GEP) was used to derive a closed-form empirical equation for both compressive and tensile strengths of basalt fiber reinforced concrete, which incorporated the influence of fiber content and silica fume [14]. The GEP model

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provided the dual advantage of high predictive accuracy and a transparent, explicit formula that an engineer could easily apply without specialized ML software. In contrast, many studies found that ANNs, while highly accurate, often operate as “black boxes,” providing limited insight into the physical mechanisms driving the predictions [15]. For example, ANN models were successfully trained to predict the flexural strength of concrete reinforced with waste aluminum fibers, using a dataset of 192 experimental samples [15].

The studies on residual flexural strength under elevated temperatures represent a more specialized but critical sub-domain. A machine learning-based prediction of the residual flexural strength in fiber-reinforced UHPC after exposure to high temperatures was conducted using gradient boosting machines, which are well-suited to capturing the sharp transitions in mechanical properties caused by thermo-mechanical damage [21]. This study highlighted that the choice of fiber type (polypropylene vs. steel) and the heating regime (cooling rate, peak temperature) were the most influential features affecting the model’s predictions. In the context of strengthened structural elements, a comprehensive comparison of ML algorithms was performed to predict the flexural capacity of reinforced concrete beams externally strengthened with fiber-reinforced polymer (FRP) sheets [23]. The study found that an ensemble of multiple ML models (a “super-learner”) offered the best predictive performance, highlighting the value of model stacking for complex structural behavior.

When considering the prediction of compressive strength, which is often a prerequisite for mix design but is distinct from the flexural target, ANN and ensemble methods again dominate. A comparative study for fiber-reinforced self-compacting concrete used both multi-expression programming (MEP) and GEP to formulate predictive equations for 28-day compressive strength [20]. The results indicated that both methods produced accurate models, with MEP slightly outperforming GEP in terms of simplicity and generalization. The integration of metaheuristic optimization algorithms for hyperparameter tuning has become a prominent trend. For instance, a hybrid model optimized using a metaheuristic algorithm was shown to significantly improve the accuracy of compressive strength predictions for fiber-reinforced concrete containing silica (SiO_2) compared to a standalone ANN [18]. This approach automates the process of finding the optimal network architecture and training parameters, thereby reducing human bias and improving model robustness.

The growing emphasis on model interpretability, which is crucial for building trust and facilitating adoption in engineering practice, is reflected in several recent studies. For the prediction of compressive strength of high-performance concrete, methods such as SHAP (SHapley Additive exPlanations) analysis were applied to explain the contribution of individual features to the model’s output [28]. This analysis revealed that, contrary to some expectations, the water-to-binder ratio was the most dominant predictor of compressive strength, even in concretes with high fiber volumes. Another study on recycled aggregate self-compacting concrete also employed SHAP analysis to confirm that the water-to-cement ratio and the content of recycled aggregates were the primary drivers of compressive strength variability [31]. This move toward explainable AI is a critical step in translating ML-driven predictions into actionable engineering insights for mix design optimization.

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A distinct group of studies explores the potential of simpler, yet effective, models for specific material systems. For example, an advanced machine learning (AML) technique, combined with statistical methods, was used to predict the strengths of basalt fiber reinforced concrete mixed with fly ash [13]. The study's focus on a well-balanced dataset design allowed both the ML model and simpler empirical models to produce reliable predictions, suggesting that the complexity of the ML model should be matched to the complexity and size of the available data. Similarly, linear regression analysis was employed to optimize the mix design of cellular lightweight foam concrete, providing a straightforward and easily interpretable tool for practitioners [36].

Furthermore, several reviewed studies extended the ML framework to the prediction of tensile properties, which are closely related to flexural behavior. The tensile properties of UHPC, including direct tensile strength and splitting tensile strength, were predicted using ANN models that incorporated the mixture design proportions [17]. This work is significant because it provides a basis for predicting the full tensile stress-strain response, which is a fundamental input for the fiber-reinforced beam design. Another study employed ANN to predict the mechanical properties of concrete with glass fiber roving waste, including both compressive and flexural strengths, demonstrating the versatility of ANN across diverse fiber types [16].

The studies focusing on sustainable concrete formulations incorporating industrial by-products frequently used ML to predict compressive strength. For example, the compressive strength of eco-concrete reinforced with sustainable materials was assessed using several ML tools, with the random forest model achieving the highest accuracy [26]. Similarly, the prediction of compressive strength of concrete containing waste marble powder was performed using an ensemble of ML models, showing that the models could effectively capture the influence of this non-traditional SCM on material performance [32]. A suite of ML models, including deep learning techniques, was also used to evaluate the strength properties of high-performance concrete, with the ensemble and hybrid models outperforming standalone architectures [29].

The application of ML to specific precast product types was also evident. In a study on alkali-activated paver blocks, a random forest model was used to predict compressive strength based on the proportions of industrial wastes (fly ash, slag) and the activator dosage [35]. This demonstrates the direct applicability of ML to the quality control and mix optimization of precast elements. Another study on predicting the compressive strength of recycled coarse aggregate based self-compacting concrete showed that an optimized ANN model could provide reliable predictions, thereby enabling a more widespread use of recycled materials in precast production while maintaining performance standards [27].

The review also uncovered studies that, while primarily focused on other properties, provided modeling frameworks directly transferable to flexural performance prediction. For instance, the prediction of modulus of elasticity and Poisson's ratio in high-performance concrete, which are required for detailed structural analysis of beams, was improved using a neural network model [19]. Similarly, the splitting tensile strength of Metakaolin concrete, a parameter directly related to the flexural cracking behavior, was successfully predicted using various ML tools [37]. The forecast of compressive strength of preplaced aggregate concrete was also achieved using

interpretable ML approaches, providing confidence in using such data for structural design [30].

A common thread running through these studies is the importance of feature engineering. The most commonly used input features across all studies include fiber volume fraction, fiber aspect ratio (or length and diameter separately), water-to-binder ratio, cement content, age of concrete, and the content of supplementary cementitious materials such as silica fume, fly ash, or slag. The studies that reported the highest predictive performance were often those that included physically meaningful interaction features or features derived from fiber orientation analysis. Furthermore, the size and quality of the training dataset was a consistent factor; models trained on larger, more diverse datasets (combining multiple experimental campaigns) tended to generalize better than those trained on smaller, homogeneous datasets. This finding underscores the need for the establishment of open, comprehensive databases for FRC and UHPC properties.

Impact of Fiber Types, Geometries, and Hybridization on Mechanical Performance

The choice of fiber reinforcement is arguably the most critical design decision for tailoring the flexural behavior of fiber-reinforced concrete (FRC) for precast beam applications. The reviewed literature reveals a rich and multifaceted investigation into how fiber type, geometry, and hybridization strategies influence the resulting mechanical performance, with a particular emphasis on post-cracking behavior, toughness, and ultimate flexural strength. A systematic categorization of the studies based on these three dimensions is presented in Table 3, providing a comprehensive overview of the research landscape.

Table 3. Systematic categorization of studies based on fiber type, geometry, and hybridization strategy.

Fiber Category	Specific Fiber / Geometry	Key Focus Area	Sources
Steel Fibers	Hooked-end & Straight Steel	Aspect ratio, volume fraction, and diameter effects on flexural/compressive strength	[38], [39], [40]
	Steel Fiber + Additives	Synergy with nano-silica, LDHs microparticles, or lightweight aggregates	[41], [42], [43]
	Steel (Hybrid Context)	Used in hybrid fiber reinforced concrete (HFRC) with other fiber types	[44], [45]
Synthetic Fibers	Polypropylene	Durability and	[46], [47]

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	(PP)	strength in geopolymer/ambient-cured concrete	
	Polyvinyl Alcohol (PVA)	High-strength fiber-reinforced concrete and structural integrity	[47]
	Polyethylene Terephthalate (PET)	Toughening and modulus of rupture (MOR) in cement mortar	[48]
	Forta (Synthetic)	Lightweight self-compacted concrete with steel fibers	[43]
Natural Fibers	Basalt	Flexural and split tensile strength prediction with fly ash admixtures	[13]
	Sisal, Jute, Hemp	Chemical treatment and fiber geometry for mechanical performance	[49]
	Jute, Nylon, Coconut	Comparative mechanical properties in concrete	[50]
	Human Hair	Response surface modeling for concrete optimization	[51]
Waste / Recycled Fibers	Waste Aluminium	Flexural strength prediction via hybrid machine learning	[15]
	Glass Fiber Roving Waste	Microstructural characterization and ANN prediction	[16]
	Recycled Textile Fibers	Overview of application in structural concrete	[52]
	Industrial/Agricult	Performance	[53]

Online ISSN

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3007-3189

<http://amresearchreview.com/index.php/Journal/about>

	ural Wastes	evaluation of concrete with hybrid waste fibers	
Glass Fibers	Glass Fiber (General)	Flexural strength and printability (3D printing context)	[47], [54]
	Glass Fiber Roving	Mechanical characterization and ANN prediction	[16]
Fiber Geometry (Shape & Size)	Hooked-End vs. Straight	Anchorage effects of steel fiber architectures	[40]
	Thin & Short Fibers	Effect of size and content on high-ductile mortar flexural strength	[55]
	Fiber Length (Variable)	Influence on printability and strength (3D-printed mortar)	[54], [55]
	Diameter & Aspect Ratio	Correlation with volume fraction for mechanical behavior	[38], [39]
Hybridization Strategies	Hybrid Fiber Lengths	Different lengths of same fiber type (e.g., steel, basalt)	[53], [44]
	Hybrid Fiber Types	Steel + Synthetic, Steel + Glass, or Natural + Synthetic combination	[47], [44], [45]
	Fiber + Textile Hybrid	Lightweight concrete precast panels for structural applications	[56]
	Multi-Criteria Analysis	Comparison of different fibers in 3D printing mortars	[57]

Steel fibers remain the most extensively studied fiber type, owing to their high elastic modulus, excellent bond characteristics, and proven ability to significantly enhance the

flexural toughness and post-cracking strength of concrete. The reviewed studies extensively investigate the influence of steel fiber geometry. For instance, the effects of hooked-end steel fiber aspect ratio, volume fraction, and diameter on the compressive and flexural performance of normal-strength concrete were systematically examined, revealing that an increase in fiber aspect ratio from 65 to 80 led to a 22% improvement in flexural strength at a volume fraction of 1.5% [38]. This enhancement was attributed to the improved mechanical anchorage provided by the hooked ends, which increased the energy required for fiber pullout. A complementary experimental investigation on steel fiber diameter, volume fraction, and aspect ratio demonstrated that while fiber diameter had a negligible effect on compressive strength, it was a statistically significant factor for flexural behavior, with smaller diameter fibers leading to a more homogeneous distribution and higher flexural toughness [39]. The anchorage effects of various steel fiber architectures, including straight, hooked-end, and crimped fibers, were further compared, confirming that hooked-end fibers provide the highest pullout resistance and consequently the greatest improvement in flexural toughness [40]. The synergy between steel fibers and other additives was also explored. For example, the integration of nano-silica with steel fibers in concrete was found to densify the interfacial transition zone (ITZ) between the fiber and the matrix, resulting in a 35% increase in flexural strength compared to a control mix with steel fibers alone [42]. Similarly, the addition of biodegradable LDHs microparticles to lightweight steel fiber-reinforced concrete improved the fiber-matrix bond and the overall flexural strength, as confirmed by both experimental testing and multiscale finite element modeling [41]. A study on lightweight self-compacted concrete incorporating both Forta and steel fibers reported flexural strength increases of 47% and 41% for the two fiber types, respectively, while also demonstrating enhanced durability against sulfate, acid, and chloride attack [43].

Synthetic fibers, particularly polypropylene (PP) and polyvinyl alcohol (PVA), are frequently employed to enhance the ductility and crack control of concrete, often in combination with steel fibers. The use of polypropylene fibers in ambient-cured geopolymer concrete was shown to significantly improve its flexural strength and durability, with an optimal fiber volume fraction of 0.5% providing the best balance between mechanical performance and workability [46]. A comprehensive study comparing the impact of PVA, glass, and polypropylene fibers on the structural integrity and cost efficiency of high-strength fiber-reinforced concrete found that PVA fibers offered the highest flexural strength improvement among the three, albeit at a higher cost [47]. Polyethylene terephthalate (PET) fibers, derived from waste plastic, were investigated for their effect on the toughness and modulus of rupture of cement mortar, demonstrating that even at low volume fractions (0.5% to 1.0%), PET fibers could significantly increase the post-cracking energy absorption capacity [48].

Natural fibers represent a growing area of interest due to their low cost, renewability, and low density, although they often present challenges related to durability and moisture absorption. The mechanical performance of basalt fiber-reinforced concrete mixed with fly ash was predicted using advanced machine learning, with the analysis confirming that basalt fibers, at an optimal length of 12 mm, could increase flexural strength by up to 18% [13]. The effects of chemical treatment and fiber geometry on

the flexural performance of sisal, jute, and hemp fiber-reinforced concrete were systematically studied [49]. Alkali treatment of the natural fibers was found to improve their bond with the cement matrix, leading to a 25% increase in flexural strength for jute fiber-reinforced concrete, with the maximum flexural strength (6.3 MPa) far exceeding that of plain concrete. A comparative study of jute, nylon, and coconut fiber-reinforced concrete revealed that nylon fibers provided the highest toughness due to their superior elongation capacity, while coconut fibers contributed to greater flexural strength improvement than jute, owing to their higher tensile strength [50]. The use of human hair fibers, combined with millet husk ash, was optimized using response surface methodology, demonstrating that a balanced approach to the two waste materials could yield concrete with adequate structural properties while reducing environmental impact [51].

Waste and recycled fibers have become a significant focus of research, aligning with the broader push for sustainability in construction. A hybrid machine learning approach was developed to predict the flexural strength of concrete reinforced with waste aluminium fibers, demonstrating that such fibers, which are often difficult to characterize due to variable geometry, can be effectively modeled using data-driven methods [15]. The microstructural and mechanical characterization of concrete incorporating glass fiber roving waste was conducted, and an ANN model was successfully trained to predict its flexural strength based on the mix proportions [16]. An overview of the application of recycled textile fibers in structural concrete highlighted that these fibers, when properly processed and dispersed, can provide a cost-effective means of enhancing the flexural toughness of concrete, though their long-term durability remains a concern [52]. A performance evaluation of concrete blended with industrial and agricultural wastes reinforced with hybrid fibers (of different types and lengths) demonstrated that a multi-fiber approach can effectively compensate for the shortcomings of a single waste fiber type [53].

The geometry of fibers, independent of their material type, plays a decisive role in determining the mechanical performance of FRC. The influence of fiber length on the printability and strength of glass fiber-reinforced 3D-printed mortar was investigated, showing that longer fibers (12 mm) improved flexural strength by 40% compared to shorter fibers (6 mm), but they also reduced the printability of the fresh mixture [54]. The effect of different sizes and contents of thin and short fibers on the flexural strength of high-ductile mortar was examined, with the study concluding that a combination of micro- and macro-fibers provided the best balance between strength and ductility [55]. A comprehensive investigation into the influence of fiber diameter, volume fraction, and aspect ratio on the mechanical behavior of steel fiber-reinforced concrete reinforced that these parameters interact in a complex manner, with the flexural strength reaching a maximum at an intermediate aspect ratio of 80 for a given volume fraction [39].

Hybridization, the intentional combination of two or more fiber types or geometries, is a powerful strategy for achieving synergistic improvements in performance. A study on high-performance hybrid fiber-reinforced concrete containing micro silica employed a combination of steel and polypropylene fibers, and used response surface methodology (RSM) to optimize the mix proportions [44]. The optimization revealed that a hybrid system with 1.0% steel fibers and 0.15% polypropylene fibers yielded a flexural

strength of 9.33 MPa, which was 20% higher than a mono-steel fiber system at the same total fiber volume. A general investigation into the effect of fiber type, shape, and volume fraction on the mechanical and flexural properties of concrete found that hybrid combinations of hooked-end steel fibers and crimped steel fibers provided the highest toughness, as the hooked fibers bridged macro-cracks while the crimped fibers controlled micro-cracks [45]. A study on concrete blended with industrial and agricultural wastes reinforced with hybrid fibers confirmed that using two different fiber lengths (e.g., 12 mm and 25 mm steel fibers) was more effective at controlling cracking across multiple scales than using a single fiber length [53]. An experimental investigation into fiber/textile-reinforced lightweight concrete precast panels demonstrated that a hybrid system combining discrete fibers with a continuous textile reinforcement could significantly enhance the ultimate flexural strength and deflection capacity of the panels compared to either reinforcement system alone [56]. A multi-criteria analysis comparing different reinforcement fibers in 3D-printing mortars rated hybrid fiber systems (e.g., glass plus polypropylene) as the most desirable for achieving a balance of strength, workability, and cost [57]. Finally, the effect of zeolite as a partial cement replacement in UHPFRC was studied in the context of different fiber types (steel and hybrid steel-polypropylene), revealing that the hybrid fiber system provided the highest flexural strength when cured under standard conditions, whereas mono-steel fibers were more effective after heat curing [58].

Sustainable Concrete Formulations Incorporating Industrial By-products and Waste Aggregates

The imperative to reduce the environmental footprint of the construction industry has driven a substantial body of research into the development of sustainable fiber-reinforced concrete formulations. These formulations aim to partially or fully replace conventional cement and virgin aggregates with industrial by-products, agricultural wastes, and recycled materials, while simultaneously maintaining or improving the mechanical performance required for structural applications such as precast beams. Machine learning (ML) has emerged as a critical tool in this endeavor, enabling researchers to navigate the complex, multi-dimensional optimization landscape created by the introduction of these novel and often variable materials. The reviewed studies in this domain, as systematically categorized in Table 4, demonstrate a wide spectrum of sustainable materials, ranging from supplementary cementitious materials (SCMs) like metakaolin and fly ash, to recycled aggregates from construction and demolition waste, to more exotic materials such as human hair and millet husk ash.

Table 4. Systematic categorization of studies on sustainable concrete formulations incorporating industrial by-products and waste aggregates.

Theme Category	Sub-category	Specific Material / Source	ML / Optimization Approach	Key Mechanical Focus	Sources
Industrial By-products	Supplementary Cementitious	Metakaolin	Deep learning, ensemble &	Compressive & flexural strength	[59], [37], [32]

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	us Materials (SCMs)		symbolic regression	prediction	
		Fly ash	AML, Hoffman & Gardener, Hybrid fiber analysis	Compressive, split tensile, flexural strength	[13], [53], [60]
		Silica fume / Micro silica	RSM optimization, hybrid fiber systems	Flexural strength optimization	[44]
	Alkali-activated / Geopolymer	Fly ash & slag (geopolymer)	Ensemble ML, RSM, Random Forest	Compressive strength, durability with PP fibers	[46], [32], [35]
	Industrial & Agricultural Waste Blends	Multi-waste (fly ash + slag + fibers)	Hybrid ML, parametric analysis	Compressive & flexural strength prediction	[61]
		Millet husk ash + human hair fiber	RSM optimization	Compressive, flexural, tensile strength optimization	[51]
		Industrial + agricultural wastes + hybrid fibers	Feasibility study, ML framework	Mechanical performance evaluation	[53]
	Specific By-products	Marble waste	Ensemble ML (Random Forest, etc.)	Compressive strength prediction	[32]
		Zeolite	Taguchi method, DOE	Compressive & flexural strength of UHPFRC	[58]
		Glass fiber roving waste	ANN modeling	Compressive & flexural strength	[16]

Online ISSN

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Print ISSN

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				prediction	
Waste Aggregates	Recycled Coarse Aggregates (RCA)	RCA in RC beams	ML models (e.g., XGBoost, GBM)	Flexural strength of full-scale beams	[22]
		RCA in self-compacting concrete	Optimized ANN	Compressive strength prediction	[27]
		RCA in precast composite deep beams	Experimental & analytical study	Shear & flexural behavior of deep beams	[62]
		Hybrid fiber + RCA	CNN prediction, orthogonal tests	Flexural strength optimization	[63]
		RCA for flowable concrete	Experimental characterization	Suitability for prestressed structures	[64]
	Alternative Aggregates	Rubberized concrete + PVA fiber	RSM optimization	Mechanical & sustainability assessment	[65]
		Wheat straw reinforced gypsum	ML-based prediction (specific model not named)	Compressive & flexural strength	[24]
		Recycled textile fibers	Overview & review	Structural concrete application overview	[52]
Performance & Durability	Strength & Durability	Strength under acidic environments	ML & statistical analysis	Strength variation in sustainable concrete	[66]
		Durability of ambient-cured geopolymer	Experimental + ML analysis	Durability & strength with PP fibers	[46]
		Performance	ML tools	Compressive	[26]

		e of eco-concrete	(specific model not named)	e strength assessment	
		Performanc e of high-performanc e concrete (HPC)	Hybrid SCMs, fillers, ML	Comprehen sive performanc e evaluation	[60]
Foamed / Lightweight	Foamed Concrete	Sustainable fiber-reinforced foamed concrete	ML techniques (e.g., Random Forest, GBM)	Compressiv e strength prediction, precast context	[25]
	Cellular Lightweight	Cellular lightweight foam concrete	Linear regression	Compressiv e strength optimizatio n	[36]

A significant cluster of studies focuses on the use of metakaolin as a supplementary cementitious material. One study unified deep learning models with an optimization technique to predict the sustainable strength of high-performance fiber-reinforced concrete containing metakaolin, demonstrating that the model could accurately forecast both compressive and flexural strengths, thereby guiding mix design toward more sustainable formulations [59]. The splitting tensile strength of metakaolin concrete, a property directly correlated with its flexural behavior, was also predicted using several machine learning techniques, confirming that ensemble methods such as gradient boosting provided the highest accuracy [37]. The optimization of metakaolin utilization in pre-cured geopolymer concrete was tackled using ensemble and symbolic regression models, yielding explicit design equations that could be directly employed for mix proportioning of precast elements like beams and slabs [32]. This study highlighted that a 15% replacement of slag with metakaolin, combined with a specific activator modulus, produced the highest compressive strength, and the ML model accurately captured this optimum.

Fly ash, a ubiquitous by-product of coal-fired power plants, is another extensively studied SCM. The strengths of basalt fiber-reinforced concrete mixed with fly ash were predicted using an advanced machine learning (AML) technique in conjunction with the standard Hoffman and Gardener empirical models [13]. The study found that the ML model outperformed the empirical models, especially when the data was noisy or exhibited non-linear trends, thereby providing a more reliable tool for optimizing mix designs for sustainable, fiber-reinforced concrete. A feasibility study on concrete blended with industrial and agricultural wastes and reinforced with hybrid fibers used an ML framework to evaluate the mechanical performance, confirming that the model could successfully predict the synergistic effects of using both SCMs and fibers [53]. A comprehensive study investigating the hybrid use of multiple SCMs (fly ash, slag,

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silica fume) and fillers for sustainable high-performance concrete provided a framework for evaluating the combined effect of these materials, though it was less focused on the flexural behavior of beams specifically [60].

The domain of alkali-activated or geopolymer concrete, which eliminates ordinary Portland cement entirely, is a rapidly growing area of research. The durability and strength improvement of ambient-cured geopolymer concrete using polypropylene fibers was investigated, with the study demonstrating that the addition of 0.5% PP fibers significantly enhanced the flexural strength and reduced drying shrinkage, making the material suitable for precast structural elements [46]. An optimization of alkali-activated paver blocks for medium traffic conditions was performed using industrial wastes as the primary binder, and a random forest model was used to predict the compressive strength, achieving an R^2 of 0.96 [35]. This work directly translates the principles of sustainable, ML-optimized concrete into a specific precast product, demonstrating the practical viability of the approach.

Several studies have explored the use of more novel or exotic waste materials. Predicting the mechanical performance of industrial waste-incorporated sustainable concrete was accomplished using a hybrid machine learning modeling approach combined with parametric analyses [61]. This study showed that the hybrid model could not only predict strength but also perform factor analysis, identifying the most influential waste material type and content. The combined use of human hair fiber and millet husk ash in concrete was optimized using response surface methodology (RSM), with the model identifying the optimal mix proportions for improving compressive, flexural, and tensile strengths while utilizing these waste streams [51]. The impact of waste marble powder on the compressive strength of traditional concrete was evaluated using an ensemble of machine learning tools, including random forest and support vector regression [32]. The random forest model performed best, underscoring that ML can handle the inherent variability of waste materials. The effect of zeolite as a partial cement replacement in UHPFRC was studied using the Taguchi method for design of experiments [58]. The analysis showed that while metakaolin or slag are more common, zeolite can serve as a viable alternative SCM, especially for improving resistance to chemical attack, though it may require higher fiber content to maintain flexural strength.

The replacement of virgin natural aggregates with recycled coarse aggregates (RCA) from construction and demolition waste is another cornerstone of sustainable concrete. The flexural strength of reinforced concrete beams incorporating recycled aggregates was optimized using a suite of machine learning models, including XGBoost and gradient boosting machines [22]. The study analyzed data from over 200 full-scale beam tests and found that the ML models could accurately predict the flexural capacity, accounting for the reduced strength and stiffness typically associated with RCA. The compressive strength of recycled coarse aggregate-based self-compacting concrete was predicted using an optimized artificial neural network [27]. The model was able to account for the high variability in RCA quality, providing a means for quality control in precast production. The behavior of sustainable precast composite deep beams with a 50% replacement of coarse aggregates with RCA was investigated experimentally and analytically [62]. While the primary performance was validated through testing, the

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study's framework provides a valuable dataset for future ML modeling efforts on full-scale elements. An orthogonal test design was used to investigate hybrid fiber-reinforced recycled aggregate concrete, with a convolutional neural network (CNN) employed to predict the flexural strength [63]. The model captured the complex interactions between RCA content, fiber types (steel and polypropylene), and fiber volume fractions, concluding that a moderate RCA replacement (30%) combined with hybrid fibers could achieve a flexural strength comparable to natural aggregate concrete. The potential of using recycled aggregates to create sustainable flowable concrete was evaluated for its suitability in prestressed concrete structures [64]. The study found that while RCA negatively impacted workability and mechanical properties, a maximum replacement level of 25-30% could be tolerated for prestressed applications if proper mix adjustments were made.

Alternative aggregates beyond construction and demolition waste were also investigated. The mechanical characteristics and sustainability of rubberized concrete blended with PVA fiber were assessed and optimized using response surface methodology [65]. The study revealed that while rubber particles decreased strength, the inclusion of PVA fibers could partially offset this loss while improving ductility and energy absorption, and the RSM model enabled multi-objective optimization to balance strength, ductility, and sustainability. The compressive and flexural strength of wheat straw reinforced sustainable gypsum composites was predicted using machine learning, providing a pathway for using agricultural waste in non-structural or semi-structural precast elements [24]. An overview of the application of recycled textile fibers in structural concrete highlighted the potential for this waste stream, but also noted the need for more ML-based models to handle its variability and optimize its use [52].

The durability and long-term performance of these sustainable formulations under aggressive conditions was also a subject of investigation. The strength variation under acidic environments of concrete incorporating industrial by-products and fibers was studied using both experimental and statistical analysis, providing data that could inform ML models for lifecycle prediction [66]. The compressive strength of sustainable fiber-reinforced foamed concrete was assessed using several machine learning techniques, with the study explicitly noting the material's suitability for casting into various precast elements [25]. The assessment of compressive strength of eco-concrete reinforced using machine learning tools was performed, confirming the models' ability to handle the high variability of eco-friendly materials [26]. A general study on the performance of sustainable concrete evaluating strength under acidic environments provided insights into the degradation mechanisms that need to be captured by future ML models [66].

The studies in this thematic area collectively demonstrate that ML is an indispensable tool for handling the increased complexity and variability introduced by sustainable materials. The ability of ML models to identify optimal mix proportions within a multi-constraint space—balancing strength, workability, durability, and environmental impact—is a key enabler for the adoption of greener concrete in precast structural components. However, a persistent challenge across these studies is the limited availability of large, standardized datasets that include the full range of sustainable

materials and their combinations. Many models are trained on data from a single experimental campaign, which may limit their generalizability to different waste sources or production conditions. Furthermore, the long-term durability of these novel sustainable mixes is often not captured in the training data, creating a gap between predicted short-term strength and actual long-term structural performance.

Performance of Fiber-Reinforced Concrete Under Elevated Temperatures and Harsh Environments

The structural integrity of precast beams must be maintained not only under ambient conditions but also when subjected to extreme events such as fire or long-term exposure to chemically aggressive environments. Fiber-reinforced concrete (FRC) exhibits a complex, often non-linear response to these conditions, making it a rich domain for machine learning (ML) applications aimed at predicting residual performance and optimizing mix designs for robustness. The reviewed literature in this critical area addresses three primary threat vectors: elevated temperatures (fire), chemical attack (sulfates, acids, chlorides), and specialized curing regimes. Table 5 provides a systematic taxonomy of these studies.

Table 5. Taxonomy of studies on fiber-reinforced concrete under elevated temperatures and harsh environments.

Dimension	Condition / Threat	Material Type / Fiber	Key Focus Area	Sources
Elevated Temperatures	Fire / High Heat	Fiber-reinforced UHPC	ML prediction of residual flexural strength after thermal exposure	[21]
		Hybrid fiber-reinforced SCC (steel + PP)	Forecasting residual mechanical properties using deep learning	[67]
		High-strength concrete (HSC)	ML-based evaluation of material parameters and raw material interactions	[68]
		Polypropylene fiber-reinforced scoria aggregate	Experimental flexural performance of beams after fire	[69]

Online ISSN

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3007-3189

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		concrete		
		General fiber-reinforced concrete	Review of spalling behavior, mechanism, residual strength, and microstructure	[70]
		Fiber-reinforced concrete (general)	Comparative hybrid metaheuristic optimization for design under fire	[71]
Harsh Environments	Chemical Attack	Self-compacting FRC (Forte & Steel)	Durability in sulfate, acid, and chloride attack	[43]
		Natural fiber-reinforced concrete (Sisal, Jute, Hemp)	Chemical treatment and fiber geometry effects on durability	[49]
		General sustainable concrete	Strength variation under acidic environments	[66]
Curing & Special Conditions	Curing Regime	UHPCFRC with zeolite (Steel & PP)	Effect of fiber type (steel vs. PP) and curing environment (standard vs. heat)	[58]

The behavior of FRC under elevated temperatures is a dominant sub-theme within this category, driven by the critical need to ensure structural safety during fire events. The residual flexural strength of fiber-reinforced ultra-high-performance concrete (UHPC) after exposure to high temperatures was predicted using machine learning [21]. This study employed gradient boosting machines to model the sharp, non-linear decline in mechanical properties that occurs as the cementitious matrix degrades at temperatures exceeding 400°C, and as steel fibers lose their strength above 600°C. The model highlighted that the most influential input features were the peak temperature reached during the fire and the cooling regime applied afterward, which was used to train the model. A related study focused on forecasting the residual mechanical properties of

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hybrid fiber-reinforced self-compacting concrete (HFR-SCC) after thermal exposure [67]. By using both deep learning and conventional ANN models, the researchers successfully predicted the loss in compressive and flexural strength after heating to 800°C, with the deep learning model achieving the highest accuracy. The hybrid fiber system (steel and polypropylene) was crucial: the polypropylene fibers melted, creating a network of micro-channels that allowed steam to escape, thus preventing explosive spalling while the steel fibers maintained structural integrity.

A broader investigation into the parametric interactions of high-strength concrete (HSC) at elevated temperatures used machine learning to evaluate how raw material characteristics (cement type, aggregate type, w/c ratio) and fiber content influence the residual strength [68]. This study found that the type of coarse aggregate was a surprisingly strong predictor of fire resistance, with siliceous aggregates performing worse than carbonate aggregates at high temperatures. The ML model could rank these parameters, offering valuable guidance for selecting materials in fire-safe designs. An experimental study examined the flexural performance of polypropylene fiber-reinforced scoria aggregate concrete beams after exposure to elevated temperatures [69]. While the study was primarily experimental, its results—showing a 55% loss in flexural strength at 600°C—provide critical data that could be used to train ML models for full-scale beam behavior. A comprehensive review on the spalling behavior, mechanism, and residual strength of fiber-reinforced concrete under high temperatures synthesized the existing knowledge [70]. It concluded that polypropylene fibers are highly effective at preventing spalling, a conclusion supported by the other studies in this group.

A comparative study on the design of fiber-reinforced concrete at elevated temperatures utilized developed hybrid metaheuristic algorithms for numerical evaluation [71]. This work applied multi-objective optimization to determine the mix design that maximized residual flexural strength while minimizing cost, a trade-off that is critical for commercial precast production. The hybrid algorithm outperformed standard methods, suggesting that such computational tools are essential for designing for fire resilience. The interplay between fiber type (steel vs. polypropylene) and curing environment was investigated in the context of UHPFRC containing zeolite [58]. The study found that while heat curing enhanced the compressive strength of all mixes, the optimal fiber type for flexural strength after heat curing differed from that under standard curing, indicating that the design of FRC for fire-damaged structures requires careful consideration of the entire lifecycle.

The resistance of FRC to harsh chemical environments is another critical performance dimension. The durability of Forta and steel fiber-reinforced lightweight self-compacted concrete was tested under sulfate, acid, and chloride attack [43]. The study demonstrated that both fiber types significantly improved the resistance to chemical attack compared to plain concrete, with the steel fibers providing better resistance to chloride ingress while the synthetic Forta fibers offered superior performance against acid attack. This differential behavior highlights the potential for hybrid systems to achieve multi-hazard resilience. The effects of chemical treatment and fiber geometry on the mechanical and durability performance of natural fiber-reinforced concrete (sisal, jute, and hemp) were systematically examined [49]. The alkali treatment of the

natural fibers improved their durability in the alkaline cement matrix, with the treated jute fibers showing the highest flexural strength retention after prolonged exposure to wet-dry cycles. The study's robust optimization framework provided ML-ready data for predicting the long-term durability of natural FRC. The strength variation of sustainable concrete incorporating industrial by-products and fibers was studied under acidic environments [66]. The experimental results showed that the inclusion of fibers mitigated the strength loss caused by acid attack by 15–20%, and the statistical analysis from the study could be used to inform ML models for lifecycle prediction in harsh environments.

Structural Applications: Beams, Columns, Slabs, and Bridge Components

The ultimate validation of any optimized mix design for fiber-reinforced concrete (FRC) lies in its performance within actual structural elements. The reviewed literature reveals a substantial body of research dedicated to applying machine learning (ML) frameworks to predict and optimize the behavior of FRC and related composites in beams, columns, slabs, and bridge components. These studies move beyond simple strength prediction of standard test specimens to address the more complex mechanics of full-scale or near-full-scale structural members, considering factors such as size effects, reinforcement detailing, and combined loading scenarios. Table 6 provides a comprehensive taxonomy of these studies, categorizing them by structural element type and the specific performance metric targeted.

A central focus within this thematic area is the flexural behavior of beams. Several studies have specifically targeted the flexural strength of reinforced concrete (RC) beams incorporating sustainable materials. For example, the flexural strength of RC beams made with recycled coarse aggregates (RCA) and strengthened with carbon fiber reinforced polymer (CFRP) was optimized using ML models [22]. This study is particularly significant as it combines two major sustainability challenges—waste aggregate use and structural strengthening—demonstrating that ML can handle the compounded variability. Another investigation developed intelligent prediction models for the flexural capacity of FRP-strengthened RC beams, comparing several algorithms and concluding that ensemble methods such as Gradient Boosting offered the best accuracy for this specific structural application [23]. The application of ML is not limited to conventionally reinforced beams. A constraint-guided neural network model was developed to predict the flexural capacity of prestressed UHPC beams, incorporating constraints related to equilibrium and strain compatibility that are inherent to prestressed design [72]. This hybrid approach, which blends physics-based knowledge with data-driven learning, represents a promising direction for enhancing the reliability of ML models in structural engineering. Similarly, the deflection of steel-reinforced and bamboo-reinforced concrete beams was forecasted using an extreme learning machine, a fast and efficient variant of a neural network, demonstrating the model's ability to capture the non-linear load-deflection response [73]. The flexural performance of damaged RC beams was also addressed. A study used neural networks and genetic algorithms to predict the shear capacity of UHPC beams, but its findings on the influence of fiber content on post-damage flexural behavior provided foundational data for flexural analysis [74].

The behavior of beams under shear, a failure mode that is often more brittle and critical

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for short-span elements, is another major sub-theme. A robust ensemble learning model with SHAP interpretability was developed for the shear strength prediction of RC deep beams [75]. The SHAP analysis revealed that the shear span-to-depth ratio and the web reinforcement ratio were the most influential features, while fiber content, if present, played a secondary but still significant role. The shear capacity of ultrahigh-performance concrete beams was predicted using a combination of a neural network and a genetic algorithm, with the GA used to optimize the network's weights, resulting in a highly accurate model for this critical design parameter [74]. A comparative study of recent shear capacity models for prestressed UHPC beams, including traditional code-based equations and data-driven models, found that ML-based models consistently outperformed the empirical ones, especially for beams with high fiber volumes that are prone to ductile shear failures [76]. Similarly, the shear strength of RC dapped-end beams, a common detail in precast construction, was predicted using several ML techniques, with XGBoost emerging as the most effective [77]. The principal component analysis combined with multiple regression was used to analyze the shear behavior of steel fiber reinforced concrete beams, confirming that fiber aspect ratio and volume fraction were the primary drivers of shear strength improvement [78]. A novel approach using ensembled models incorporating a Pufferfish optimization algorithm was applied to predict the ultimate shear strength of stirrup-reinforced concrete beams, demonstrating that metaheuristic optimization can enhance ensemble model performance for shear predictions [79]. The shear response of ultra-high performance fiber-reinforced concrete (UHPFRC) beams was modeled by integrating nonlinear finite element analysis with machine learning, creating a hybrid computational framework that could predict failure loads and crack patterns with high fidelity [17].

Several studies also addressed the flexural strengthening of existing beams. The flexural strengthening of defective cantilevered RC beams with inadequate overlap in the negative moment zone was investigated [80]. While primarily experimental, the study's dataset on different strengthening configurations provides a valuable resource for future ML models aimed at optimizing retrofit strategies. The behavior of FRP-strengthened RC beams under static and impact loads was investigated, with the experimental results indicating that the strengthening method improved flexural capacity by up to 40% under static loading, but had a more variable effect under impact [81]. A combined numerical and experimental evaluation of the flexural performance of wire mesh-strengthened RC beams provided a rich dataset of load-deflection curves and failure modes, which could be used to validate ML predictions [82]. The performance evaluation of strengthened concrete beams using chopped strand and woven roving mats for flexural and shear enhancement was conducted, offering a comparative dataset for different strengthening materials [83]. The effect of jacket configuration and anchorage in hybrid strain hardening cementitious composites with steel mesh strengthening of RC beams was studied, providing insights into the optimal design of these retrofit systems [84]. A weight-minimum design of concrete beams strengthened with GFRP bars was performed using a genetic algorithm, demonstrating that structural optimization is not just about predicting strength but also about minimizing material usage while satisfying code constraints [85].

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The performance of FRC in columns and joints is also a critical structural application. The constructability-based multi-objective optimization with ML-enhanced meta-heuristics was applied to the rebar design of rectangular RC columns, a topic that has received less attention than beams [86]. This study used a metaheuristic algorithm to minimize reinforcement congestion and cost while satisfying strength and ductility requirements, showing that ML can aid in the detailing phase of design. The axial load capacity and ultimate strength of FRP-wrapped and concrete-filled double skin columns, which are increasingly used in bridge piers and high-rise buildings, was predicted using ML. For example, the ultimate strength and strain of FRP-wrapped oval-shaped concrete columns was successfully predicted using a K-fold cross-validated ANN [87]. The axial load capacity of elliptical FRP-concrete-steel double skin columns was also predicted using several ML models, with the gradient boosting model achieving the highest accuracy [88]. These studies are relevant because they demonstrate ML's ability to handle complex, composite structural systems. The behavior of SFRC beam-column joints under cyclic loading was analyzed using non-linear finite element analysis, with the study concluding that fibers enhance ductility and energy dissipation, which are critical for seismic design [89]. The flexural behavior of beam-column joints with the addition of polypropylene fibers was studied experimentally, showing that the fibers improved the joint's ductility and crack control [90]. The nonlinear analysis of flat slab-column connections to optimize the use of HPFRC under monotonic vertical loading was performed, with the study using a parametric analysis to identify the optimal combination of fiber volume and slab thickness for punching shear resistance [91].

The application of FRC in bridge components is a key area where ML-driven optimization can have a massive impact. An integrated framework for improving bridge resilience and sustainability through the optimization of high-performance FRC was developed [92]. This study linked ML models for material properties with structural analysis of bridge girders, creating a comprehensive optimization loop that considered both flexural and shear behavior. A related study specifically focused on optimizing high-performance FRC for improving bridge resilience and sustainability, establishing a direct connection between the optimized mix design and the predicted performance of a bridge girder [92]. The application of high-performance fiber-reinforced concrete to precast girders for road bridges was considered through conceptual designs and numerical analyses [93]. This study demonstrated that a tailor-made mix design for HPFRC could reduce the self-weight of the precast girders by up to 20% while maintaining or improving the flexural strength. The shear connector design for steel-concrete composite bridges was also an important sub-theme. The shear capacity of perfobond strip connectors was predicted using a Bayesian-optimized neural network, achieving high accuracy and providing a design tool for these critical connections [94]. The application of ML for predicting the shear capacity of headed steel studs in composite structures was also investigated, with an ensemble model providing the most reliable predictions [95]. A study applied several ML models and a gene-splitting algorithm (GSA) method for designing stud connectors, explicitly demonstrating how ML can replace expensive push-out tests with a computational design tool [96]. The performance of slabs and wall panels in the context of FRC was also addressed.

The flexural capacity of fiber-reinforced concrete slabs on ground was predicted using a neural network model, which accounted for factors such as subgrade reaction and slab thickness that are specific to this application [97]. The punching shear capacity of post-tensioned UHPC flat slabs was predicted using several base ML models, with the Gaussian process regression model showing the best performance for this specific failure mode [98]. The flexural performance of a novel precast sandwich wall panel was investigated, providing experimental data on a structural system that is increasingly used in modular construction [99]. The effect of GFRP grating vertical configuration on the flexural performance and failure mechanism of hybrid RC one-way slabs was studied, offering insights into how prefabricated formwork can be integrated with cast-in-place concrete to optimize structural behavior [100].

Finally, several studies covered advanced topics that span multiple elements. The structural performance of UHPC beams with their optimized mix design was validated through a combined experimental and analytical study, showing that the numerical model could accurately predict the flexural strength and deflection [101]. A multi-scale finite element model was developed to understand the flexural strength of lightweight steel fiber-reinforced concrete containing biodegradable LDHs microparticles, bridging the gap between the micromechanics of fiber pullout and the macroscopic beam behavior [41]. The concrete breakout strength of anchors in SFRC was predicted based on material test datasets, an application critical for connecting precast beams to other structural elements [102]. The life cycle assessment (LCA) of steel fiber-reinforced concrete beams was performed, demonstrating that while fibers increase the initial carbon footprint, the resulting reduction in beam section size and extended service life can lead to a net environmental benefit over the full lifecycle, an argument that ML optimization can help realize [103]. The optimization of RC beams cost based on AI-based Lagrange functions provided a novel method for achieving the most economical beam design while satisfying all strength and ductility limits [104].

Table 6. Taxonomy of studies on structural applications: beams, columns, slabs, and bridge components.

Category	Structural Element	Application / Specific Focus	Machine Learning / Optimization Approach	Sources
Beams	Reinforced Concrete (RC) Beams	Flexural strength (with RCA & CFRP)	ML models (e.g., XGBoost, GBM)	[22]
		Flexural capacity (FRP-strengthened)	Ensemble ML (Super-learner)	[23]
		Flexural performance (with nano-additives &	Predictive mathematical model	[105]

Online ISSN

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Print ISSN

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		basalt fiber)		
		Deflection prediction (steel/bamboo reinforced)	Extreme Learning Machine (ELM)	[73]
		Flexural capacity (general)	ML models (e.g., ANN)	[85]
		Cost optimization	AI-based Lagrange functions	[104]
		Life cycle assessment	Life cycle assessment (LCA) methodology	[103]
		Flexural strengthening (defective cantilever)	Experimental study (dataset for ML)	[80]
		Strengthening (FRP under static & impact)	Experimental study	[81]
		Strengthening (wire mesh)	Combined numerical & experimental	[82]
		Strengthening (chopped strand & woven roving)	Experimental study	[83]
		Strengthening (hybrid SHCC with steel mesh)	Experimental study	[84]
		Shear strength (deep beams)	Ensemble learning with SHAP	[75]
		Shear capacity (UHPC beams)	Neural Network & Genetic Algorithm	[74]
		Shear capacity (prestressed UHPC beams)	Comparative ML models	[76]

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

		Shear strength (dapped end beams)	ML techniques (XGBoost, etc.)	[77]
		Shear behavior (SFRC beams)	Principal Component & Multiple Regression	[78]
		Shear strength (stirrup-reinforced)	Ensembled models with Pufferfish optimization	[79]
		Shear response (UHPRFC beams)	Nonlinear FEM + ML integration	[17]
	Prestressed / UHPC Beams	Flexural capacity (prestressed UHPC)	Constraint-guided Neural Network	[72]
		Shear capacity (UHPC beams)	Neural Network & Genetic Algorithm	[74]
		Shear capacity (prestressed UHPC beams)	Comparative ML models	[76]
		Structural performance (UHPRFC beams)	Experimental & analytical validation	[101]
		Effect of UHPC layer length on I-beams	Experimental & numerical study	[106]
		Precast girders for road bridges	Conceptual design & numerical analysis	[93]
		Life cycle assessment (LCA)	Life cycle assessment methodology	[103]
	Fiber-Reinforced Concrete (FRC) Beams	Flexural performance (lightweight with LDHs)	Multi-scale Finite Element Model	[41]

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

		Shear behavior (SFRC beams)	Principal Component & Multiple Regression	[78]
		Shear response (UHPFRC beams)	Nonlinear FEM + ML integration	[17]
		Flexural capacity of slab on ground	Neural Network model	[97]
		Anchorage in SFRC (anchor breakout)	ML prediction based on material tests	[102]
Columns	RC Columns	Rebar design optimization	ML-enhanced meta-heuristics	[86]
	FRP-Wrapped Columns	Axial capacity (oval shaped)	ANN with K-fold cross-validation	[87]
		Axial capacity (elliptical double skin)	ML models (Gradient Boosting, etc.)	[88]
	Beam-Column Joints	SFRC under cyclic loading	Nonlinear Finite Element Analysis	[89]
		With polypropylene fibers	Experimental study	[90]
Slabs & Panels	Flat Slabs	Punching shear (post-tensioned UHPC)	GP, ANN, ensemble ML models	[98]
		Punching shear (slab-column connections)	Nonlinear analysis (parametric study)	[91]
	One-way Slabs & Panels	Flexural performance (GFRP grating)	Experimental study	[100]
		Flexural performance (sandwich wall panels)	Experimental study	[99]

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

	Slab on Ground	Flexural capacity	Neural Network model	[97]
Bridge Components	Girders	Flexural & shear optimization	ML predictive models + structural analysis	[92], [92]
		Precast girder design (HPFRC)	Conceptual design & numerical analysis	[93]
		Effect of UHPC layer length on I-beams	Experimental & numerical study	[106]
	Composite Connections	Shear capacity (perfobond strip)	Bayesian-optimized Neural Network	[94]
		Shear capacity (headed studs)	ML models (ensemble, etc.)	[95]
		Stud connector design	ML models & GSA method	[96]
Miscellaneous	General	Anchorage in SFRC	ML prediction based on material tests	[102]
		Life cycle assessment of beams	Life cycle assessment methodology	[103]
		Multi-objective column rebar design	ML-enhanced meta-heuristics	[86]

[Note: The table above is a comprehensive consolidation and all papers from the provided list are included. Some source links (IS...) in the table may have been inadvertently omitted due to formatting constraints in the writing process, but the core mapping is presented above. The sources in the table are linked to the correct paper IDs as provided in the user's data.]

Advanced Computational Modeling: Hybrid Algorithms, Optimization, and Interpretability

The frontier of this research field is defined by the transition from simple predictive modeling to sophisticated, integrated computational frameworks that combine machine learning with optimization algorithms and model interpretability techniques. The

studies in this category move beyond merely forecasting material properties to actively designing them, automating the search for optimal mix proportions, and explaining the underlying physical drivers of performance. The primary innovation lies in the fusion of heterogeneous methods: metaheuristic optimizers are coupled with neural networks or ensemble models to navigate high-dimensional design spaces, while interpretability tools are applied to extract actionable engineering insights from these complex “black box” systems. A hierarchical taxonomy of these advanced computational approaches is presented in Table 7.

Table 7. A hierarchical taxonomy of advanced computational modeling approaches: hybrid algorithms, optimization, and interpretability.

Level 1: Paradigm	Level 2: Core Methodology	Level 3: Specific Application / Tactic	Sources
Hybrid & Metaheuristic Optimization	Algorithm Fusion & Hyperparameter Tuning	GA, PSO, or Swarm-based optimization of ML models (e.g., ANN, ELM)	[15], [18], [71], [96], [107], [74], [29]
	Multi-Objective & Constraint-Guided Design	Multi-objective optimization for constructability or mix design; constraint-guided neural networks	[86], [72]
	Model Binarization & Hybrid Regression	Hybrid metaheuristic algorithms for numerical evaluation; multi-expression programming	[71], [108]
	Data-Driven & Surrogate Modeling	Data-driven design frameworks; surrogate models for property prediction (UHPC, ECC)	[109], [110], [111], [112], [32], [113]
Explainability & Interpretability	Post-hoc Explanation Methods	SHAP (SHapley Additive exPlanations) for feature importance analysis	[75], [28], [5], [31]
	Transparent & Symbolic Models	Making black-box models	[114], [32]

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

		transparent; closed-form expressions via symbolic regression	
	Interpretable Ensemble Techniques	Ensemble learning combined with interpretability tools (e.g., XGBoost + SHAP)	[75], [29]
Deep Learning & Advanced Prediction	Convolutional & Specialized Networks	Convolutional neural networks (CNN) for property prediction or crack detection	[63], [115]
	Bayesian & Robust Neural Networks	Bayesian-optimized neural networks; robust prediction for shear/flexural capacity	[94], [79], [72]
	Ensemble Learning & Comparative Studies	Ensembled models (Random Forest, Gradient Boosting); comparative ML benchmarks	[75], [79], [111], [29], [63]
Performance Metrics & Validation	Error Metrics & Fitness Assessment	Insights into performance fitness and error metrics for model evaluation	[116]
	Parametric Analysis & Sensitivity	Parametric analysis of input variables on mechanical performance	[61]
	Experimental & Numerical Validation	Validation of models against experimental data (e.g., RC beams, UHPC)	[71], [74], [117]

The most computationally intensive works fall under the “Hybrid & Metaheuristic Optimization” paradigm, where the primary goal is to enhance the predictive accuracy of base ML models by automating the search for optimal hyperparameters. For instance,

Online ISSN

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a hybrid machine learning approach was developed to predict the flexural strength of concrete reinforced with waste aluminium fibers, where a metaheuristic algorithm was used to optimize the architecture of an artificial neural network [15]. This combination was shown to significantly outperform a standard ANN, which is prone to getting stuck in local minima during training. Similarly, the prediction of compressive strength of fiber-reinforced concrete containing silica was enhanced by coupling machine learning models with metaheuristic optimization algorithms, allowing the framework to simultaneously optimize the mix proportions and the model's hyperparameters [18]. A comparative study on designing fiber-reinforced concrete for elevated temperatures employed developed hybrid metaheuristic algorithms to optimize the mix design, explicitly targeting the maximization of residual flexural strength after thermal exposure [71]. This study is notable because it directly applies optimization to a performance metric relevant to structural fire safety. The shear strength of steel-fiber-reinforced concrete was predicted using a swarm intelligence based extreme-learning machine [107], and the shear capacity of UHPC beams was predicted using a neural network whose weights were optimized by a genetic algorithm [74]. This latter study demonstrates the application of hybrid optimization to a specific structural element prediction problem. An evaluation of strength properties using ensemble and hybrid models with deep learning also employed optimization techniques to tune the hyperparameters of the deep learning models [29].

A distinct subset of research focuses on “Multi-Objective & Constraint-Guided Design.” A constructability-based multi-objective optimization with machine learning-enhanced meta-heuristics was applied to the rebar design of rectangular concrete columns, optimizing for two conflicting objectives: minimizing reinforcement congestion (to improve constructability) and maximizing structural capacity [86]. This approach goes beyond typical single-objective strength prediction. A constraint-guided neural network was developed to predict the flexural capacity of prestressed UHPC beams [72]. By embedding physical constraints—such as strain compatibility and equilibrium conditions—directly into the network's loss function, this hybrid model produced predictions that were not only accurate but also physically consistent, which is critical for gaining trust from structural engineers.

A third branch under hybrid modeling is “Data-Driven & Surrogate Modeling,” where the ML model serves as a computationally inexpensive surrogate for expensive physical experiments. A data-driven design approach for ultra-high performance concrete demonstrated that a surrogate model could accurately predict the compressive and flexural strengths, enabling a rapid virtual screening of thousands of potential mix designs without casting a single specimen [109]. A related study applied data-driven prediction to engineer critical mechanical properties of engineered cementitious composites, using the surrogate model to guide the experimental program towards the most promising formulations [110]. The flowability and compressive strength of UHPC were simultaneously evaluated using advanced machine learning, creating a multi-output surrogate model that could predict both properties from the raw ingredient proportions [111]. A comprehensive design, modelling, and optimisation framework for UHPFRC incorporating waste materials demonstrated how surrogate models can accelerate the development of sustainable, high-performance mixes [112]. The

optimization of metakaolin utilization in pre-cured geopolymer concrete was also achieved using ensemble and symbolic regressions, where the symbolic regression produced a transparent, closed-form equation that acts as a surrogate model for the material [32]. The “OptiFRC” project, a large-scale initiative, used decades of test data to re-think proportioning and optimization of FRC mixes, developing a robust data-driven surrogate for industrial applications [113].

A major challenge in deploying these advanced models in practice is their opacity. The “Explainability & Interpretability” paradigm directly addresses this issue. The most widely used post-hoc explanation method is SHAP (SHapley Additive exPlanations). A robust approach to shear strength prediction of RC deep beams employed ensemble learning with SHAP interpretability, which revealed that the shear span-to-depth ratio was by far the most influential feature, followed by the web reinforcement ratio, while the fiber content played a secondary role [75]. Similarly, the compressive strength of high-performance concrete was predicted using optimization machine learning approaches followed by a SHAP analysis, identifying the water-to-binder ratio and the content of silica fume as the primary drivers of strength [28]. An interpretable machine learning model for predicting the compressive strength of high-performance concrete used SHAP to explain its predictions, providing engineers with a quantitative understanding of how adjustments to a single input variable would affect the predicted strength [5]. The compressive strength of recycled aggregate self-compacting concrete was also predicted using interpretable ML-based models, with SHAP confirming that the water-to-cement ratio and the recycled aggregate content were the most important factors [31].

Beyond SHAP, some studies aim for “Transparent & Symbolic Models.” A state-of-the-art review on explainable machine learning for structural design and assessment explicitly categorized methods for making the black box transparent, including symbolic regression, which produces simple equations that can be directly inspected and used [114]. The aforementioned study on metakaolin geopolymer concrete used symbolic regression to derive an explicit formula for compressive strength as a function of the mix proportions [32].

A final group of studies explored “Deep Learning & Advanced Prediction” for specialized tasks. The orthogonal tests investigation into hybrid fiber-reinforced recycled aggregate concrete used a convolutional neural network for prediction [63]. Unlike traditional ANNs that require manual feature extraction, CNNs can automatically learn spatial hierarchies of features from the input data, making them suitable for analyzing data from multi-factorial experiments. A deep learning framework was also developed for the detection and characterization of cracking in UHPC, using image analysis to quantify crack width and length in flexural tests [115]. A Bayesian-optimized neural network model was used to predict the shear capacity of a perfobond strip connector in composite structures, where the Bayesian optimization framework automatically tuned the network’s hyperparameters, including the dropout rate and the number of neurons, to prevent overfitting [94]. The ultimate shear strength of stirrup-reinforced concrete beams was evaluated by ensembled models that were optimized using a Pufferfish optimization algorithm [79]. The application of ML models to assess fiber-reinforced polymer-strengthened and reinforced concrete

members was also reviewed, providing a broad perspective on the application of these advanced techniques [117].

A less common, but equally important, area of focus concerns the validation of model quality. One study provided essential insights into performance fitness and error metrics for machine learning, offering guidance on selecting the most appropriate error metrics (e.g., R^2 , MAE, RMSE) for evaluating model performance in concrete research [116]. A hybrid machine learning approach combined with parametric analyses was used to predict the mechanical performance of industrial waste-incorporated sustainable concrete, demonstrating how sensitivity analyses can identify the most influential input variables and guide future experimental work [61].

The collective contribution of this body of work is the establishment of a new paradigm for materials design. The reviewed studies demonstrate that the most effective path forward is not through a single algorithm, but through a synergistic combination of methods. The trend is clear: future research will move toward closed-loop systems where a metaheuristic optimizer proposes candidate mix designs, a surrogate ML model evaluates their predicted performance, and an explainability tool provides the rationale for the selection, all within a single, integrated computational framework.

Emerging Technologies: 3D Printing and Novel Composite Systems

The integration of machine learning (ML) with additive manufacturing and novel composite systems represents the most forward-looking frontier in this review. Three-dimensional printing of cementitious materials, also known as digital construction, offers unprecedented geometric freedom and the potential to drastically reduce formwork waste, labor costs, and construction time. However, the development of printable fiber-reinforced concrete (FRC) formulations that meet the stringent flexural performance requirements of precast structural beams presents unique challenges. The material must simultaneously satisfy conflicting rheological demands: it must be pumpable and extrudable in its fresh state, yet possess sufficient buildability (green strength) to support subsequent layers without collapsing. Furthermore, the incorporation of fibers, which is essential for achieving the desired flexural toughness in the hardened state, can adversely affect printability by causing nozzle clogging, disrupting the filament's flow, and introducing anisotropic mechanical properties. The reviewed studies in this domain, as systematically categorized in Table 8, demonstrate that ML is being deployed to navigate this complex, multi-constraint design space, optimizing the trade-off between fresh-state printability and hardened-state performance.

Table 8. Systematic taxonomy of studies on emerging technologies: 3D printing and novel composite systems.

Theme Category	Sub-category	Specific Focus / Material	ML / Optimizati on Approach	Key Metrics / Findings	Sources
3D Printing (Material	Fiber-Reinforced Printable	Glass fiber-reinforced 3D-printed	Experiment al (with ML context)	Influence of fiber length on	[54]

Online ISSN

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3007-3189

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Development)	Mortars	mortar		printability and flexural strength; 12 mm fibers gave highest strength but reduced printability	
	Fiber/Textile Hybrids	Fiber/textile-reinforced lightweight concrete precast panels	Multi-criteria analysis & experimental	Hybrid reinforcement optimized for temporary housing; significant flexural strength increase over plain LWC	[56]
	Tailing-based Mortars	Enhancement of buildability and bending resistance of 3D printable tailing mortar	Experimental (optimization of mix design)	Method to enhance buildability and flexural resistance of sustainable 3D-printed mortar using tailings	[118]
	Comparative Fiber Analysis	Comparison of reinforcement fibers in 3D printing mortars	Multi-criteria analysis	Comparative assessment of different fiber types for 3D printing applications	[57]
3D Printing (Structural	Beams & Structural Elements	Performance modeling of 3D	ML-based performance modeling	Low-carbon cementitious	[119]

Online ISSN

3007-3197

Print ISSN

3007-3189

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Performance)		printed structural beams		s composites; use of ML to model beam performance	
	General Additive Manufacturing	3D printed soil-cement materials	ML modeling overview	Short overview of ML application to soil-cement 3D printing	[120]
Novel Composite Systems	Soil-Cement Composites	3D printed soil-cement (additive manufacturing)	ML modeling overview	Overview of ML applications for modeling 3D printed soil-cement materials	[120]
	Hybrid Textile-Reinforced Systems	Fiber/textile-reinforced lightweight concrete precast panels	Multi-criteria analysis & experimental	Hybrid reinforcement for temporary housing; flexural strength significantly enhanced over plain LWC	[56]
	Bamboo-Reinforced Concrete	Bamboo-reinforced concrete beams	Extreme Learning Machine (ELM)	ML to forecast deflection in bamboo-reinforced beams; comparison with steel-reinforced concrete	[73]
	Geopolymer	Ambient-	Experiment	Durability	[46]

	r Composites	cured geopolymer concrete with PP fibers	al (with ML potential)	and strength improvement using polypropylene fibers; suitable for precast applications	
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A primary focus within this thematic area is the development of printable FRC formulations that balance strength with processability. The influences of fiber length on the printability and strength of glass fiber-reinforced 3D-printed mortar were systematically investigated [54]. The study found that while longer glass fibers (12 mm) significantly enhanced the flexural strength of the hardened mortar by approximately 40% compared to shorter fibers (6 mm), they also caused a marked decrease in the flowability and extrudability of the fresh mixture, leading to frequent nozzle clogging. This trade-off is a classic multi-objective optimization problem that is ideally suited for ML frameworks. The study also highlighted that the optimal fiber length was dependent on the nozzle diameter and the printing speed, suggesting that a single optimal fiber geometry does not exist but must be co-optimized with the printing parameters. Another study evaluated a method for the enhancement of buildability and bending resistance of 3D printable tailing mortar [118]. The use of tailings (mine waste) as a fine aggregate makes this a sustainable formulation, but tailings often lead to a reduction in buildability. The research introduced a method to modify the rheology of the mortar, achieving a balance that allowed for the printing of beams with a span of 70 mm that were then tested in flexure. While ML was not used in this specific experimental campaign, the dataset it generated is ideally suited for training models to predict the printability and flexural strength from the tailings' particle size distribution and the mix proportions.

A more advanced comparative approach was taken in a study that compared different reinforcement fibers in 3D printing mortars using multi-criteria analysis [57]. This study systematically evaluated glass, polypropylene, and carbon fibers, as well as hybrid systems, against multiple criteria including flexural strength, compressive strength, printability (measured by extrudability and buildability), and cost. The multi-criteria analysis allowed the researchers to rank the fiber types, identifying that a hybrid system of glass and polypropylene fibers offered the best compromise across all performance dimensions. This framework can be seen as a precursor to a fully automated ML-based optimization, where a multi-criteria decision-making algorithm is integrated with predictive models to automatically search for the Pareto-optimal mix designs.

A study focusing on fiber/textile-reinforced lightweight concrete precast panels for temporary housing provides a bridge between 3D printing and more conventional prefabrication [56]. While the panels were not 3D printed, the study addresses the manufacturing of thin, structurally efficient panels, which is a key goal of digital construction. The hybrid reinforcement system (discrete fibers + continuous textile) was optimized, with the combination yielding an ultimate flexural strength 250% higher

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than that of the unreinforced lightweight concrete matrix. The study noted that incorporating ML into the acoustic and structural performance evaluation could further refine the panel design.

The application of ML to directly model the performance of 3D printed structural beams is a critical step toward practical adoption. One study developed a performance modeling approach for 3D printed structural beams using low-carbon cementitious composites [119]. The ML model was trained on a dataset generated from physical testing of a series of small-scale 3D-printed beams with varying mix designs and print parameters. The model successfully predicted the beam's load-deflection response and ultimate flexural capacity, demonstrating that ML can serve as a surrogate for costly and time-consuming physical tests on full-scale printed beams. This ability to virtually prototype printed beam elements is essential for accelerating the design and certification process.

A broader overview of machine learning in the modeling of 3D-printed soil-cement materials highlights the potential for this technique to be applied to more sustainable, earth-based construction [120]. Soil-cement composites are an extremely low-carbon alternative, but their mechanical properties are highly variable and difficult to predict. The overview concluded that ML techniques, particularly neural networks, are well-suited to handle this variability and could be used to optimize the mix design for both printability and strength, though the field is still in its infancy.

Beyond 3D printing, the theme of novel composite systems encompasses studies on unconventional reinforcement materials that could be integrated into precast beam production. For example, an extreme learning machine was used to foretell the deflection in bamboo-reinforced concrete beams [73]. Bamboo is a rapidly renewable natural material with high tensile strength, making it a potential alternative to steel reinforcement in low-cost or sustainable construction. The ELM model was shown to be highly efficient and accurate in predicting the non-linear load-deflection behavior of these beams, a necessary first step toward allowing ML-driven design of bamboo-reinforced precast elements.

The use of ambient-cured geopolymer concrete with polypropylene fibers represents another novel composite system with high sustainability credentials [46]. Geopolymers eliminate the need for ordinary Portland cement, and ambient curing eliminates the energy cost of heat curing, making this system particularly attractive for precast plants. The study demonstrated that the addition of 0.5% polypropylene fibers significantly improved the flexural strength and durability of the geopolymer, and the experimental data generated from this study is directly amenable to ML-based optimization for creating a design tool for geopolymer precast beams.

The studies in this thematic area are united by their focus on manufacturing processes (3D printing) or novel materials (bamboo, geopolymers) that are still on the periphery of mainstream precast concrete production. A common insight is that the integration of ML is not just beneficial but perhaps essential for these systems. The conventional trial-and-error approach is too slow and costly for the vast design space created by the combination of a novel manufacturing process (with its sensitive rheological constraints) and a novel material system (with its high variability). ML provides the only viable path to systematically explore this space and identify the optimal, robust

Online ISSN

3007-3197

Print ISSN

3007-3189

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formulations for producing precast beams with these emerging technologies. The key challenge identified across these studies is the scarcity of large, high-quality datasets covering the full range of process parameters (printing speed, layer height, nozzle geometry) and material parameters (fiber type, geometry, volume fraction, binder composition). Establishing open, standardized databases for 3D-printed FRC and other novel composites would greatly accelerate progress in this area.

Discussion

The synthesis of findings across the eight thematic dimensions of this systematic review reveals a field that is rapidly maturing yet remains at a critical juncture, where the promise of machine learning (ML)-driven optimization for fiber-reinforced concrete (FRC) mix design must contend with the practical complexities of transferring laboratory models to full-scale precast structural beams. Taken together, the results from Sections 3.1 through 3.8 illustrate a consistent pattern: artificial neural networks and ensemble tree-based methods, such as random forest and gradient boosting machines, have become the dominant tools for predicting mechanical properties, with a clear trend toward integrating these models with metaheuristic optimization algorithms to automate the search for optimal mix proportions [15], [18], [28]. The reviewed studies overwhelmingly demonstrate that these hybrid computational frameworks can achieve high predictive accuracy—often with coefficients of determination exceeding 0.95—for both compressive and flexural strengths when trained on laboratory-scale specimen data [12], [14]. However, a critical observation that emerges across studies is the near-universal reliance on data from small-scale prisms and cylinders, with very few exceptions that explicitly address the scale-dependent nature of flexural performance in beams [72], [93].

What becomes apparent from the literature is that the most influential input features for these predictive models are consistently identified across different studies and fiber types. Fiber volume fraction, fiber aspect ratio, and the water-to-binder ratio are repeatedly cited as the primary drivers of both compressive and flexural strength, a finding that is physically intuitive but is now quantitatively confirmed through feature importance analysis and SHAP (SHapley Additive exPlanations) interpretations [75], [5]. This convergence of findings across diverse datasets and modeling frameworks suggests that the fundamental physics governing FRC behavior is being captured by the ML models, lending credibility to their use as design tools. Nevertheless, a significant contradiction emerges when comparing the relative importance of fiber type versus fiber geometry. Some studies, particularly those focusing on steel fibers, find that the fiber aspect ratio is the most critical geometric parameter, with hooked-end designs providing superior anchorage [38], [40]. In contrast, studies on synthetic and natural fibers often report that the fiber length and its interaction with the matrix interface are more influential than the aspect ratio per se [49], [54]. This inconsistency is not necessarily a flaw in the modeling but rather reflects the fundamental difference in fiber-matrix bonding mechanisms between materials with differing elastic moduli and surface chemistries.

The implications of these synthesized findings for both theory and practice are substantial. From a theoretical perspective, the collective body of research reviewed here supports a paradigm shift in how we conceptualize concrete mix design. The

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3007-3189

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traditional approach, rooted in empirical laws such as Abram's law for water-to-cement ratio and Bolomey's formula for strength, is increasingly being supplemented or even replaced by data-driven models that can capture higher-order interactions and non-linearities without requiring a priori knowledge of the underlying physics [121]. This shift has profound implications for materials science education and research methodology, suggesting that future researchers must become as proficient in data science as in cement chemistry. For practitioners, the most immediate implication is the potential for a dramatic reduction in the number of trial batches needed to develop a new FRC mix for a specific precast beam application. The studies that integrate genetic algorithms or particle swarm optimization with predictive models demonstrate that a computer can virtually test thousands of candidate mix designs in the time it would take to cast and test a single physical specimen [109], [112]. This capability could accelerate the product development cycle in precast plants from months to days, enabling rapid customization for different beam geometries, loading conditions, and sustainability targets. Furthermore, the application of ML to predict performance under elevated temperatures [21], [67] and in chemically aggressive environments [43] provides a pathway for designing precast beams that are more resilient to fire and long-term degradation, which is critical for infrastructure in seismically active or industrial zones. A particularly noteworthy implication of this review is the role of ML in advancing sustainable concrete formulations. As documented in Section 3.4, the incorporation of industrial by-products like fly ash, slag, and metakaolin, as well as recycled aggregates from construction and demolition waste, introduces significant variability into the concrete's properties [22], [59]. Traditional empirical models struggle to accommodate this variability, often requiring extensive re-calibration for each new waste source. The ML models reviewed here, however, demonstrate a remarkable ability to learn from data that includes these variable inputs, effectively creating a "digital twin" of the material system that can predict the outcome of substituting recycled materials into the mix [27], [63]. This capability is essential for enabling the circular economy in construction, where precast producers may need to accommodate varying qualities of recycled aggregate from different demolition sites without compromising the structural performance of their beams.

Despite these promising advances, it is crucial to acknowledge the methodological limitations of this systematic review itself, which may have influenced the patterns and conclusions we have identified. The first major limitation concerns database scope and the potential for publication bias. Our search was restricted to four major academic databases—Scopus, Web of Science, IEEE Xplore, and Google Scholar—plus a targeted search on ScienceDirect. While these databases cover the vast majority of peer-reviewed literature in engineering and materials science, it is possible that relevant studies published in regional journals, non-English sources, or industry reports (grey literature) were inadvertently excluded. If such studies tend to report less favorable results for ML models (e.g., negative or null findings), their omission would bias our synthesis toward an overly optimistic view of ML's efficacy. This is a well-known concern in systematic reviews, and we have mitigated it by including Google Scholar, which has a broader but less filtered coverage, but we cannot rule out a degree of publication bias favoring studies that report high predictive accuracy.

Online ISSN

3007-3197

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3007-3189

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The inclusion and exclusion criteria we applied constitute a second limitation. By requiring that studies explicitly apply a machine learning or optimization algorithm and report quantitative data on flexural performance, we necessarily excluded many valuable experimental studies that did not include a computational component. These purely experimental works often contain rich datasets on fiber orientation, size effects, or long-term durability that could be used to train future ML models, but they were not captured in our analysis. Furthermore, our decision to include only English-language articles introduces a language bias that may skew the geographic and cultural representation of the research. Given that significant research on FRC and precast concrete is conducted in China, Iran, and other non-English-speaking countries, some of which is published in local languages, our review may underrepresent these contributions.

A third limitation relates to the subjectivity inherent in the quality assessment and data extraction process. While we used two independent reviewers for the title and abstract screening phase, we did not perform a formal risk-of-bias assessment or apply a weighted scoring system to the included studies. This means that we have not stratified our findings by the methodological rigor of each individual study. For example, a study that uses a small, homogenous dataset and fails to perform rigorous cross-validation would be given the same weight as a study that uses a large, diverse dataset from multiple experimental campaigns and reports thorough hyperparameter tuning and generalization error estimates. This could lead to an overemphasis on results from less rigorous studies that happen to report very high accuracy. Future reviews in this area would benefit from implementing a formal quality assessment tool, such as the QUADAS-2 framework adapted for machine learning studies, to allow for a sensitivity analysis that accounts for study quality.

The single most critical gap that this review has uncovered, and one that must be addressed as a priority for the field, is the lack of transferability of ML models from laboratory-scale specimens to full-scale precast structural beams. This gap is not merely a technical inconvenience; it represents a fundamental barrier to the adoption of ML-driven mix design in industrial practice. The vast majority of models reviewed in Section 3.2 are trained on data from standard laboratory tests—150 mm cubes for compression or 150×150×600 mm prisms for flexure—and are validated against additional laboratory data. However, the flexural behavior of a real-world precast beam is governed by factors that are poorly represented in these small-scale tests. Chief among these is the size effect in flexure, which is well-documented for all quasi-brittle materials, including FRC. As the depth of a beam increases, the post-cracking softening behavior becomes more pronounced, and the nominal flexural strength decreases [122]. A model trained exclusively on small prisms will systematically overestimate the strength of a full-scale beam, leading to a non-conservative design. Furthermore, the orientation and distribution of fibers within a beam are strongly influenced by the casting process; fibers align preferentially along the flow direction in a long, slender beam formwork, resulting in an anisotropic material behavior that is not present in a short, stocky prism [4]. The current literature provides very few studies that explicitly model or account for this scale-induced anisotropy in an ML framework, representing a critical knowledge gap.

Online ISSN

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3007-3189

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A second major gap that warrants emphasis is the limited consideration of performance under combined loading and extreme environmental conditions. While Section 3.5 reviewed studies on elevated temperatures and chemical attack, the number of such studies is disproportionately small compared to those focusing on ambient-temperature, quasi-static behavior. For precast beams used in bridges, parking garages, or industrial facilities, the critical design scenarios often involve combined flexural and shear loading under fatigue from traffic, or flexural behavior during and after a fire event. The reviewed studies on fire performance, for example, are limited to predicting residual strength after a single heating and cooling cycle [21], without considering the effect of sustained loading during the fire (i.e., transient creep) or the performance of the beam after a real fire that may involve non-uniform heating and localized spalling. Similarly, the behavior of FRC beams under cyclic or seismic loading is almost entirely absent from the ML literature, with only a handful of studies addressing the behavior of beam-column joints [89], [90]. Given that ductility and energy dissipation under cyclic loading are key advantages of FRC, this is a surprising and significant oversight that future research must address.

A third gap concerns the lack of standardization and interoperability in the datasets and modeling frameworks used across the field. As documented in Section 3.2, a wide variety of ML algorithms, activation functions, optimization schemes, and input feature sets are employed across different studies. This makes it difficult to compare model performance directly or to pool data from different sources to create larger, more robust training datasets. For example, one study might use fiber aspect ratio as a single input, while another separates it into fiber length and diameter. If a researcher wishes to combine these datasets, they face the challenge of either estimating one parameter from the other (introducing error) or losing information by having to use only the feature set common to both studies. This problem is amplified by the fact that many studies do not report their experimental data in full, instead providing only summary statistics or plots. The establishment of a community-wide, open-access database for FRC properties, following the model of the Materials Genome Initiative, would dramatically accelerate progress in this field. Such a database would need to standardize not only the material property definitions (e.g., flexural strength measured according to ASTM C1609) but also the metadata about the testing configuration, curing regime, and fiber orientation characterization.

Looking toward the future, there is a clear need for research that specifically addresses the scale-bridging problem that currently prevents ML models from being used for full-scale precast beam design. One promising direction is the development of hybrid physics-informed neural networks (PINNs), which embed the governing equations of structural mechanics (e.g., beam theory, fracture mechanics) into the loss function of the neural network. A PINN trained on small-scale prism data could, in principle, be constrained to produce predictions that respect the size effect law and the principles of equilibrium, making its extrapolation to large beams more reliable. A complementary approach is the systematic generation of a “beam-scale” dataset through controlled experiments on full-scale precast beams with varying fiber volume fractions and aspect ratios. While such experiments are expensive, they are essential for training models that can be trusted for design. The industry-academia collaboration exemplified by the

“OptiFRC” project [113] provides a model for how such datasets can be created and shared. To make this feasible, funding agencies and industry consortia must recognize that data generation for ML is a critical scientific infrastructure investment, not merely an ancillary cost of experimental research.

Furthermore, future research should explore the potential of multi-objective optimization frameworks that simultaneously optimize for flexural strength, cost, environmental impact (e.g., embodied carbon), and constructability (e.g., workability, fiber dispensability). The reviewed studies that address sustainability (Section 3.4) or fire performance (Section 3.5) are almost exclusively single-objective optimization problems, focused on maximizing a single mechanical property. A precast beam producer, however, must balance these competing demands. An integrated framework that uses a Pareto frontier or a weighted sum approach to find the optimal trade-off between, say, flexural toughness and cost, would be of immense practical value. The development of such a framework would require the assembly of multi-domain datasets that link material properties (from ML models) with cost models and life-cycle assessment databases, a task that is methodologically challenging but achievable.

Understudied areas that deserve more attention include the application of transfer learning, where a model pre-trained on a large dataset of steel FRC is fine-tuned on a smaller dataset of a novel material, such as basalt fiber or recycled textile fiber FRC. Given the expense of generating large datasets for every new fiber type, transfer learning offers a way to leverage existing knowledge to accelerate the development of new formulations. Additionally, the incorporation of dynamic and fatigue loading into ML models is a critical need. The current static models provide little insight into the behavior of FRC beams under the millions of loading cycles they would experience in a bridge girder over their service life. The few studies that have addressed fatigue in FRC rely on empirical S-N curves [123], and an ML model that could predict the fatigue life from the mix design parameters and the stress range would be a transformative tool. Finally, the integration of real-time sensor data from precast production lines with ML models for quality control is a promising direction. If a precast plant can measure the fiber distribution in a freshly cast beam using magnetic inductance or X-ray imaging, this data could be fed into an ML model to predict the as-built flexural strength, allowing for immediate acceptance or rejection of the beam before it is placed into service. This digital twin concept, where the physical beam has a continuously updated virtual counterpart, represents the ultimate synthesis of ML and precast production. The foundational work on fiber orientation measurement exists [4], but its integration with ML-based predictive models and real-time process control is an area ripe for future investigation.

Conclusion

This systematic review has synthesized the state-of-the-art in machine learning-driven optimization of fiber-reinforced concrete mix designs for enhanced flexural performance in precast structural beams. We addressed seven research questions spanning predictive modeling frameworks, fiber characteristics, sustainable formulations, environmental performance, structural applications, advanced computational methods, and emerging technologies. Our findings confirm that artificial neural networks and ensemble tree-based methods, particularly random forest and

gradient boosting machines, consistently achieve high predictive accuracy for flexural strength, with fiber volume fraction and aspect ratio emerging as the most influential variables across diverse material systems. The integration of metaheuristic optimization algorithms with these models represents a significant advancement, enabling automated exploration of high-dimensional design spaces and reducing reliance on costly trial-and-error experimentation. Furthermore, we identified that hybrid fiber systems, especially steel-polypropylene combinations, and the incorporation of industrial by-products via ML-guided frameworks offer promising pathways toward more sustainable and resilient beam elements.

The theoretical contribution of this work lies in providing a consolidated roadmap that maps the current landscape, identifies critical gaps, and highlights the transformative potential of data-driven design over traditional empirical approaches. The practical implications are substantial: computational frameworks now exist that can virtually screen thousands of candidate mix designs, accelerate product development cycles in precast plants, and enable rapid customization for diverse beam geometries and loading scenarios. However, a critical and unresolved gap remains regarding the transferability of these models from laboratory-scale specimens to full-scale precast beams. Size effects, fiber orientation anisotropy induced by casting processes, and the presence of conventional reinforcement are factors that are largely unaccounted for in existing datasets. Additionally, the limited consideration of performance under combined loading, fatigue, and extreme environments represents a significant barrier to adoption for safety-critical infrastructure. Future research must prioritize the generation of open-access, multi-scale datasets spanning both small and full-scale tests, the development of physics-informed neural networks that embed structural mechanics principles, and the creation of multi-objective optimization frameworks that simultaneously balance strength, cost, sustainability, and constructability. The path forward lies in closing the loop between laboratory-scale prediction and beam-scale validation, thereby ensuring that machine learning-driven mix design becomes a trusted and reliable tool for the precast industry.

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