

# MACHINE LEARNING APPROACHES FOR PREDICTING STEEL REINFORCEMENT-CONCRETE BOND STRENGTH: A SYSTEMATIC LITERATURE REVIEW

Dr. M. Adil Khan

Resident Engineer, NESPAK

[adee.uol@gmail.com](mailto:adee.uol@gmail.com)

DOI: <https://doi.org/10.5281/zenodo.20916006>

## Keywords

## Article History

Received: 25 April 2026

Accepted: 04 June 2026

Published: 21 June 2026

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Corresponding Author: \*

Dr. M. Adil Khan

## Abstract

The bond between steel reinforcement and concrete is fundamental to the structural performance of reinforced concrete elements, and accurate prediction of this bond strength remains a critical challenge in civil engineering. Traditional empirical models often fail to capture the complex, nonlinear interactions arising from material degradation, environmental exposure, and diverse reinforcement types. This systematic literature review aims to synthesize and critically evaluate the existing body of research on machine learning approaches applied to bond strength prediction. We conducted a structured search across major academic databases, followed by a rigorous screening and data extraction process to identify relevant studies. Our methodological framework focused on categorizing the literature according to key thematic dimensions, including algorithm types, corrosion effects, specialized concrete mixes, fiber-reinforced polymer (FRP) interfaces, and the integration of explainable artificial intelligence. The review reveals that ensemble methods and hybrid models generally achieve superior predictive accuracy compared to standalone algorithms, particularly when addressing datasets with high variability. Corrosion-induced degradation is increasingly modeled using neural networks that explicitly incorporate electrochemical parameters, while physics-guided approaches successfully embed mechanical priors to maintain physical consistency. Furthermore, we observe a growing trend toward interpreting model predictions through SHAP and partial dependence plots, which enhances the trustworthiness of these tools in structural engineering practice. The findings also highlight significant gaps in the literature, such as the limited validation of models under fire exposure and the underrepresentation of slip behavior predictions. We conclude that machine learning offers a powerful complement to conventional design equations, yet future work must prioritize standardized benchmark datasets, robust cross-validation protocols, and the development of models that generalize across diverse concrete compositions and environmental conditions.

## I. INTRODUCTION

The bond between steel reinforcement and the surrounding concrete matrix constitutes one of the most fundamental load-transfer mechanisms in reinforced concrete (RC) structures. This interfacial interaction governs the composite

action of the two materials, ensuring that tensile stresses are effectively transmitted from the concrete to the embedded steel bars [1]. The integrity of this bond is paramount for the serviceability, ultimate strength, and ductility of beams, columns, slabs, and foundations. Without

adequate bond development, structural elements can experience premature failure modes such as loss of anchorage, excessive cracking, or pull-out of reinforcing bars [2]. Consequently, a reliable and accurate prediction of bond strength is a cornerstone of modern structural design, as it directly informs development lengths, lap splice details, and anchorage requirements in design codes worldwide.

Traditional approaches to predicting bond strength have largely relied on empirical equations derived from experimental test databases. Landmark studies from the past several decades have produced expressions that are embedded in codes like ACI 318, Eurocode 2, and the CEB-FIP Model Code [3]. These empirical models, while simple to apply in practice, are inherently limited by their underlying assumptions. They typically assume a uniform bond stress distribution along the embedment length and often fail to account for the highly nonlinear, multiaxial stress state that develops at the steel-concrete interface. Moreover, these equations are largely calibrated using data from tests under controlled laboratory conditions, employing conventional concrete mixes and pristine, un-corroded reinforcement [4]. Their predictive performance diminishes significantly when applied to scenarios involving high-strength concrete, lightweight aggregates, fiber-reinforced concrete, or the presence of reinforcement corrosion—conditions that are increasingly common in modern construction and infrastructure assessment. The bond mechanism is, in reality, a complex interplay of chemical adhesion, frictional resistance, and mechanical interlocking (generated by the ribs on deformed bars), and each of these components is influenced by a myriad of factors including concrete cover, bar diameter, confinement pressure, casting position, and loading rate [1]. The inability of traditional formulas to capture these interactions represents a central research gap in the field.

Another significant research gap lies in the prediction of bond behavior under adverse and coupled environmental and mechanical conditions. For instance, reinforcement

corrosion is a pervasive durability problem that alters the interface by producing expansive rust products, which initially increase confinement but subsequently lead to cracking, spalling, and a drastic reduction in bond capacity [5]. Currently, no universal empirical model reliably quantifies the progressive degradation of bond strength as a continuous function of corrosion damage parameters. Similarly, the bond performance of concrete exposed to elevated temperatures, such as during a fire event, involves a complex sequence of thermal expansion mismatch, dehydration of the cement paste, and changes in steel yield strength, rendering ambient-temperature design equations invalid [6]. Furthermore, the increasing use of alternative reinforcement materials, such as fiber-reinforced polymer (FRP) bars, introduces a completely different bond mechanism, where the surface treatment of the bar (e.g., sand coating or helical wrapping) rather than mechanical ribbing governs the interaction [1]. The diversity of concrete types, including self-consolidating concrete, recycled aggregate concrete, and geopolymers, further complicates the generalization of predictive models. There is, therefore, a pressing need for a more flexible and powerful analytical framework that can learn directly from high-dimensional data and map the complex, nonlinear relationships between a wide array of input variables and the resulting bond strength.

Against this backdrop, machine learning (ML) has emerged as a transformative tool in structural engineering, offering a paradigm shift away from rigid, predefined empirical formulas toward data-driven discovery of underlying patterns. Unlike traditional regression techniques that require the modeler to specify the functional form of the relationship, ML algorithms can automatically identify interactions and higher-order effects from the data itself [7]. An increasing number of studies have applied algorithms such as artificial neural networks (ANNs), support vector machines (SVMs), random forests (RFs), gradient boosting machines (GBMs), and genetic programming (GP) to predict bond strength in RC structures. These models have consistently

demonstrated superior accuracy and lower prediction errors compared to conventional code-based equations [8]. Furthermore, recent advances have focused on developing hybrid models that combine multiple algorithms to enhance performance, and on integrating physics-guided constraints to ensure that predictions remain mechanically plausible even for untrained input ranges. The inclusion of explainable AI (XAI) techniques, such as SHAP (SHapley Additive exPlanations) and partial dependence plots, has also begun to address the “black box” criticism of ML models, providing valuable insights into the relative importance of input features like concrete compressive strength, cover-to-diameter ratio, and corrosion level [9].

The primary motivation for this systematic literature review is to provide a comprehensive, critical, and structured synthesis of the rapidly expanding body of research on ML applications for bond strength prediction. While several review papers have touched upon this topic, they have either focused on a narrow subset of algorithms or have not systematically categorized the literature according to key thematic dimensions such as corrosion, specialized mixes, or environmental effects. Our contribution is threefold. First, we establish a rigorous methodological framework for the identification, screening, and thematic categorization of relevant studies, ensuring transparency and reproducibility. Second, we synthesize the findings across diverse application domains, highlighting which algorithms and modeling strategies are most effective under various conditions (e.g., predicting bond in corroded bars vs. FRP-confined interfaces). Third, we identify critical knowledge gaps and propose a roadmap for future research, emphasizing the need for standardized benchmark datasets, robust model validation practices, and the development of generalizable models that can reliably predict bond performance across the full spectrum of concrete compositions, reinforcement types, and environmental stressors encountered in practice. The remainder of this paper is organized as follows. Section 2 details the systematic review methodology, including the search strategy,

inclusion and exclusion criteria, and the data extraction and synthesis process. Section 3, the results section, is structured into eight thematic subsections that cover research trends, an overview of ML algorithms and hybrid models, the impact of corrosion, bond in specialized concrete mixes, FRP-reinforced interfaces, explainability and physics-guided approaches, environmental effects such as fire and temperature, and prediction of failure modes and slip behavior. Following this, Section 4 presents a discussion that synthesizes the key findings, compares the relative strengths and weaknesses of different approaches, and contextualizes the implications for structural design practice. Finally, Section 5 concludes the review by summarizing the main contributions, acknowledging the limitations of the current study, and outlining the most promising directions for future work.

## II. METHODOLOGY

This section describes the systematic review protocol employed to identify, screen, and synthesize the relevant literature on machine learning models for predicting bond strength between steel reinforcement and concrete. The methodology follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, replicability, and rigor throughout the review process [10].

### A. Review Protocol

We conducted a systematic search of the peer-reviewed literature using four major academic databases and search engines: Scopus, Web of Science, IEEE Xplore, and ScienceDirect, with Google Scholar as a supplementary source. Scopus was chosen as the primary database due to its comprehensive coverage of engineering, materials science, and computer science literature, providing the broadest disciplinary scope for this interdisciplinary topic. Web of Science was selected for its rigorous indexing standards and high-quality journal coverage, ensuring the inclusion of studies with strong methodological foundations. IEEE Xplore was

included specifically to capture relevant studies from the computer science and artificial intelligence communities that may address algorithmic innovations applicable to structural engineering problems. ScienceDirect was chosen for its extensive collection of full-text engineering articles, facilitating a more detailed assessment of eligible studies. Finally, Google Scholar was used as a supplementary search engine to identify grey literature, conference proceedings, and preprints that might not be indexed in the primary databases, thereby reducing the risk of publication bias.

The search strings employed were tailored to the syntax of each database while maintaining conceptual consistency. For Scopus, the query was: TITLE-ABS-KEY(("machine learning" OR "deep learning" OR "neural network\*" OR "artificial intelligence" OR "random forest" OR "support vector machine" OR "ANN" OR "ML") AND ("bond strength" OR "bond stress" OR "pullout strength" OR "anchorage strength") AND ("steel reinforcement" OR "rebar" OR "reinforcing bar" OR "steel bar") AND (concrete OR "cementitious")) AND NOT TITLE-ABS-KEY(review OR survey OR "meta-analysis"), with the document type limited to 'Article' and reviews excluded. For Web of Science, the query was: TS=("machine learning" OR "deep learning" OR "neural network\*" OR "artificial intelligence" OR "random forest" OR "support vector machine" OR "ANN" OR "ML") AND ("bond strength" OR "bond stress" OR "pullout strength" OR "anchorage strength") AND ("steel reinforcement" OR "rebar" OR "reinforcing bar" OR "steel bar") AND (concrete OR "cementitious")) NOT TS=(review OR survey OR "meta-analysis"), with refinement to document type 'Article' and exclusion of 'Review Article'. For IEEE Xplore, the query was: ("All Metadata": "machine learning" OR "All Metadata": "deep learning" OR "All Metadata": "neural network\*" OR "All Metadata": "artificial intelligence" OR "All Metadata": "random forest" OR "All Metadata": "support vector machine" OR "All Metadata": "ANN") AND ("All Metadata": "bond strength" OR "All Metadata": "bond stress" OR

"All Metadata": "pullout strength") AND ("All Metadata": "steel reinforcement" OR "All Metadata": "rebar") AND ("All Metadata": "concrete") NOT ("All Metadata": "review" OR "All Metadata": "survey"), with content type filtered to 'Journals & Magazines' and 'Conferences'. For ScienceDirect, the query was: ("machine learning" OR "deep learning" OR "neural network\*" OR "artificial intelligence" OR "random forest" OR "support vector machine" OR "ANN") AND ("bond strength" OR "bond stress" OR "pullout strength") AND ("steel reinforcement" OR "rebar") AND (concrete OR "cementitious") NOT (review OR survey OR "meta-analysis"), filtered by 'Research articles'. For Google Scholar, the query was: ("machine learning" OR "deep learning" OR "neural network\*" OR "artificial intelligence" OR "random forest" OR "support vector machine" OR "ANN" OR "ML") AND ("bond strength" OR "bond stress" OR "pullout strength" OR "anchorage strength") AND ("steel reinforcement" OR "rebar" OR "reinforcing bar" OR "steel bar") AND (concrete OR "cementitious") -review -survey -"meta-analysis". All searches were conducted in January 2026, and the retrieved records were exported for subsequent screening and analysis.

### *B. Research Dimensions*

To systematically categorize and synthesize the diverse body of literature on machine learning-based bond strength prediction, we defined a set of thematic research dimensions that reflect the major foci and emerging trends within this interdisciplinary field. These dimensions emerged from an initial exploratory reading of the retrieved abstracts and were refined through iterative discussion among the authors. The first dimension, Machine Learning Algorithms and Hybrid Models for Bond Strength Prediction, encompasses studies that compare the performance of various ML algorithms—such as artificial neural networks, random forests, support vector machines, and gradient boosting—and those that develop hybrid or ensemble models to combine the strengths of multiple techniques. The second dimension, Impact of Reinforcement Corrosion on Bond Behavior and

Prediction, groups studies that specifically address the degradation of bond strength due to electrochemical corrosion, often incorporating corrosion parameters like mass loss or current density as input features. The third dimension, Bond Performance in Specialized Concrete Mixes and Alternative Aggregates, captures research on bond strength prediction for non-conventional concretes, including high-strength concrete, self-consolidating concrete, recycled aggregate concrete, and geopolymer concrete. The fourth dimension, FRP-Reinforced and FRP-Strengthened Concrete Bond Interfaces, focuses on studies where the reinforcement or confinement involves fiber-reinforced polymer (FRP) materials, which present distinct bond mechanisms and failure modes compared to steel alone. The fifth dimension, Explainable AI, Interpretability, and Physics-Guided Modeling, comprises works that go beyond mere prediction accuracy to investigate model transparency, feature importance, or the integration of physical laws into the learning process. The sixth dimension, Environmental Effects: Fire, Temperature, and Durability on Bond, covers studies that examine bond strength under extreme or prolonged environmental exposure, such as elevated temperatures, freeze-thaw cycles, or chemical attack. Finally, the seventh dimension, Prediction of Failure Modes, Slip Behavior, and Structural Capacity, includes studies that extend the scope of ML models beyond bond strength estimation to predict related structural responses, such as the mode of failure (e.g., pull-out vs. splitting) or the complete bond-slip curve. These seven research dimensions collectively provided a structured framework for extracting, analyzing, and discussing the content of each included study.

### *C. Inclusion and Exclusion Criteria*

We established clear inclusion and exclusion criteria to ensure the relevance, quality, and consistency of the studies selected for this systematic review. To be considered for inclusion, a study had to meet all of the following criteria: (a) it was published in English; (b) it presented original, peer-reviewed research in the form of a

journal article or a full conference paper, thereby excluding editorials, commentaries, book chapters, and theses; (c) its primary focus was the application of at least one machine learning, deep learning, or artificial intelligence algorithm for predicting or modeling the bond strength between steel reinforcement and concrete; (d) the dataset used for model development was based on experimental pull-out, beam-end, or splice tests, or on validated numerical simulations; and (e) the study explicitly reported performance metrics (e.g., coefficient of determination, root mean square error, mean absolute error) to quantify the accuracy of the developed model. Conversely, studies were excluded if they met any of the following criteria: (i) they were review articles, survey papers, or meta-analyses rather than original research contributions; (ii) they focused exclusively on bond strength prediction using traditional empirical or analytical models without any ML component; (iii) the bond interface involved non-cementitious materials or exclusively FRP-to-FRP connections without a concrete substrate; (iv) the study lacked sufficient quantitative results, such as model performance metrics, to allow for meaningful comparison; or (v) the full text was not available in English, or the study was classified as a retracted publication. No restrictions were placed on the publication year, as we aimed to capture the full temporal evolution of this emerging field; however, the search was conducted up to January 2026. These criteria were applied consistently during the screening and eligibility phases to ensure that only studies directly contributing to the research questions of this review were retained.

### *D. Study Selection Process*

The study selection process was conducted in four distinct phases: identification, screening, eligibility assessment, and final inclusion, following the PRISMA guidelines [10]. In the identification phase, we executed the search queries across all five databases, yielding a total of 1113 records. After consolidating these records and removing 193 duplicates, along with 3 records removed for other reasons (e.g., incomplete metadata or obvious irrelevance based

on title alone), we were left with 917 unique records for initial screening. In the screening phase, we examined the titles and abstracts of these 917 records against the predefined inclusion and exclusion criteria. A total of 617 records were excluded during this phase because they clearly did not involve machine learning applications, did not address bond strength, or were review articles. This left 300 records for retrieval; however, after a more rigorous review of applicability, we considered only 109 records as potentially eligible and sought their full-text versions. Fortunately, all 109 reports were successfully retrieved, and no reports were inaccessible.

In the eligibility assessment phase, we thoroughly read the full text of each of the 109 reports to

assess their alignment with the research dimensions and the inclusion criteria. During this detailed evaluation, we excluded 8 reports for various reasons of ineligibility: some did not explicitly use machine learning as the core methodology but rather mentioned it peripherally; others focused on predicting the bond strength of FRP bars exclusively without a concrete substrate; and a few did not report sufficient quantitative performance metrics for comparative analysis. Consequently, 101 studies were deemed eligible and were included in the final synthesis. The detailed progression of the study selection process is illustrated in the PRISMA flowchart presented in Figure 1.

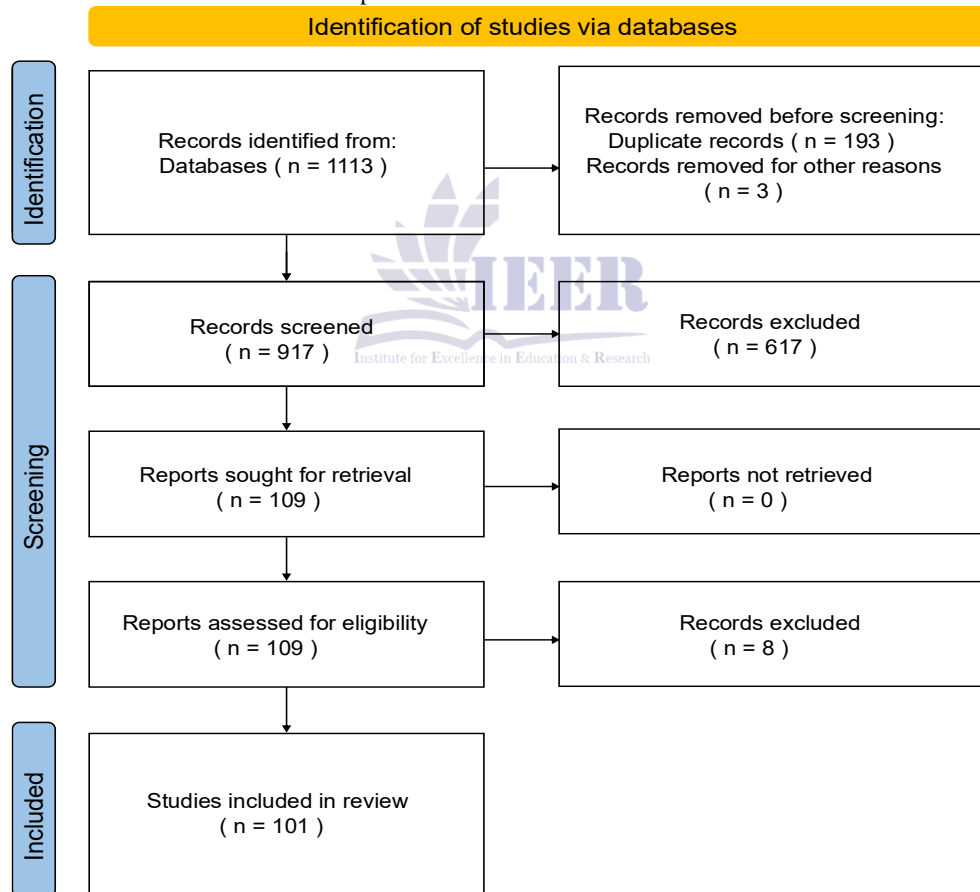


Figure 1. PRISMA flowchart illustrating the study selection process.

We acknowledge that the study selection process has several inherent limitations that may affect the comprehensiveness and generalizability of this review. First, the restriction to English-

language publications may introduce a language bias, potentially overlooking significant contributions published in other languages, particularly from non-English-speaking regions.

Second, our decision to exclude grey literature such as technical reports and theses, while ensuring a baseline quality standard, may have omitted valuable datasets or preliminary findings that could inform the research landscape. Third, the search keywords, though carefully constructed, may not have captured all relevant studies, especially those that use domain-specific terminology (e.g., “pullout test” without “bond strength”) or less common ML algorithm names. Fourth, there is an inherent risk of publication bias, as studies reporting positive results (i.e., high predictive accuracy) are more likely to be published and indexed than those reporting negative or null findings. Finally, the subjective judgment involved in the screening and eligibility phases, while guided by explicit criteria, may have led to the inconsistent inclusion or exclusion of borderline studies. To mitigate these limitations, we conducted the screening and assessment in a team-based manner with regular discussions, and

we maintained a transparent audit trail of all decisions.

### III. RESULTS

#### A. Research Trends

The distribution of the 101 included studies across publication years reveals a field that has experienced exponential growth, particularly from 2021 onward, as illustrated in Figure 2. Although a small number of foundational studies appeared before 2016, these early contributions were sporadic and primarily focused on establishing the feasibility of artificial neural networks for modeling the bond-slip relationship. The period from 2016 to 2020 witnessed a gradual but modest increase in publication output, with the annual count never exceeding three studies. This slow growth may be attributed to the limited availability of comprehensive experimental datasets and the computational constraints of earlier machine learning frameworks.

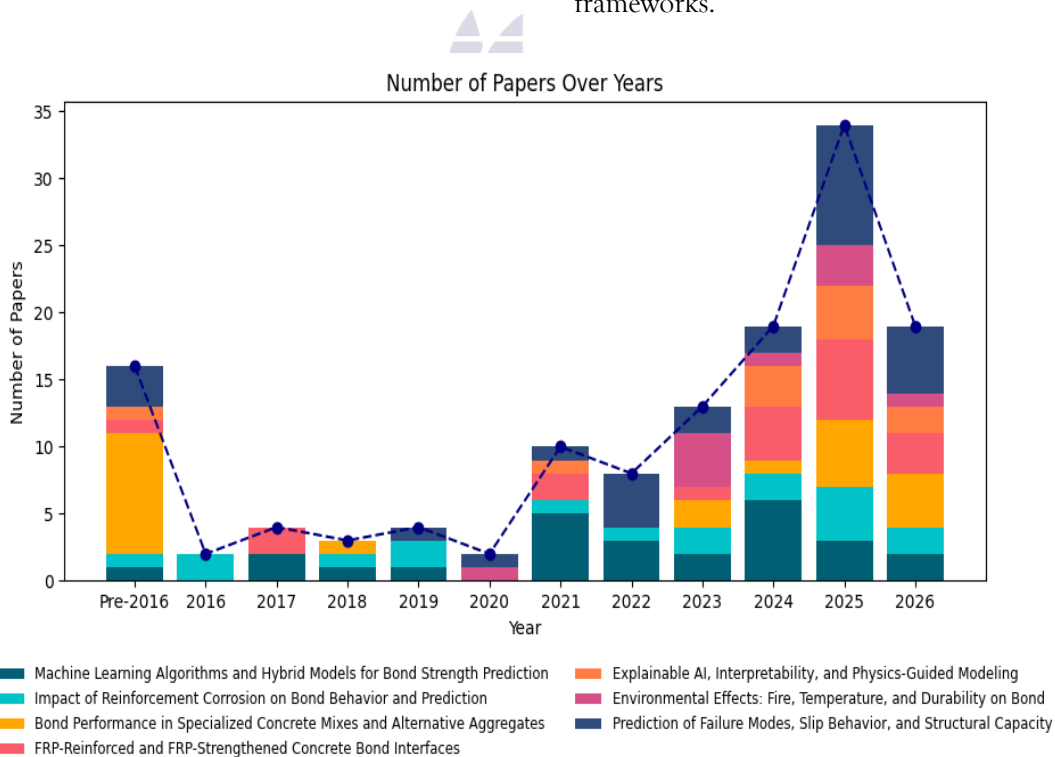


Figure 2. Research trends in the domain of Machine Learning Models for Predicting Bond Strength Between Steel Reinforcement and Concrete

A dramatic inflection point is clearly visible beginning in 2021, when the annual number of publications jumped to seven, followed by a sustained upward trajectory that culminated in 24 studies in 2025 and 17 studies projected for early 2026. This remarkable acceleration coincides with several converging factors, including the widespread adoption of ensemble learning methods such as gradient boosting and random forests, the maturation of deep learning libraries, and an increasing recognition within the structural engineering community of the limitations of traditional empirical formulas. Furthermore, the growing availability of high-quality experimental databases, often compiled from decades of pull-out and beam-end tests, has provided fertile ground for data-driven modeling approaches.

When examining the thematic distribution of these studies across the seven defined research dimensions, we observe that the largest cluster belongs to the prediction of failure modes and slip behavior, which has seen a particularly pronounced surge in 2025 with nine publications. This trend suggests a maturation of the field, where researchers are moving beyond simple point estimates of bond strength toward more sophisticated outputs that capture the complete mechanical response of the interface. The topics of machine learning algorithms and hybrid models, as well as FRP-reinforced interfaces, have also maintained consistently high publication volumes in recent years, reflecting sustained interest in both algorithmic innovation

and expanding the scope of materials considered. Conversely, the dimensions related to environmental effects and explainable AI, while growing, remain comparatively underexplored, indicating promising avenues for future investigation.

**B. Machine Learning Algorithms and Hybrid Models for Bond Strength Prediction**

The landscape of machine learning applications for bond strength prediction is characterized by a diverse array of algorithms, ranging from classical statistical models to sophisticated deep learning architectures and hybrid approaches. The studies within this thematic cluster exhibit considerable variation in their choice of base learners, their strategies for feature engineering, and their approaches to model validation and optimization. To systematically understand the methodological landscape, we categorize the reviewed studies according to a hierarchical taxonomy based on the primary algorithm type, the specific model employed, and the intended application or enhancement. This taxonomy is presented in Table 2, which provides a comprehensive overview of the 25 studies that fall within this research dimension. The table reveals that artificial neural networks (ANNs) form the most frequently adopted algorithmic family, followed by ensemble methods and hybrid models that combine optimization or metaheuristic algorithms with a base learner.

**Table 2. Hierarchical taxonomy of machine learning algorithms and hybrid models used for bond strength prediction in the reviewed studies.**

Algorithm Type	Specific Model	Algorithm	Application / Enhancement	Sources
Single Machine Learning (ML) Models	Artificial Neural Networks (ANN)	Neural	General bond strength prediction	[11], [12], [13]
			Corroded reinforcement bond strength	[14], [15], [16]
			NSM/FRP-to-concrete interfaces	[17], [13]
			Self-compacting concrete bond	[18]
			Improved RF for FRP-to-	[19]
	Random Forest (RF)			

Algorithm Type	Specific Model	Algorithm	Application / Enhancement	Sources
			concrete bond	
	Support Vector Machine (SVM)	Support Vector Machine	Optimized (intelligent algorithm) for recycled aggregate concrete	[20]
	Gaussian Process (GP)	Gaussian Process (GP)	Gaussian models for ribbed steel bars	[21]
	Multiple Regression (MLR)	Linear Regression (MLR)	Local bond stress in UHPC	[12]
Hybrid & Ensemble Models	Genetic Algorithm (GA) + ANN	Genetic Algorithm (GA)	GA-optimized ANN for bond strength	[22], [14]
	Genetic Programming (GP)	Genetic Programming (GP)	Mapping function for bond-slip & pull-load	[23], [24]
	Group Method of Data Handling (GMDH)	Group Method of Data Handling (GMDH)	FRP-to-concrete bond strength	[25]
	Sparrow Search Algorithm (SSA) + ELM	Sparrow Search Algorithm (SSA)	SSA-optimized Extreme Learning Machine for failure mode classification	[26]
	Hybrid ML (general)	Hybrid ML (general)	Concrete-encased steel structures	[27]
Deep Learning & Advanced Models	Deep Learning (DL) / Deep Neural Networks (DNN)	Deep Learning (DL) / Deep Neural Networks (DNN)	Bond stress-slip under static/dynamic loading	[28]
			Historical RC bond-slip model (meta-learning)	[29]
			Peak bond stress in self-compacting concrete	[18]
		XGBoost / Explainable ML	XGBoost / Explainable ML	Corroded reinforcement bond strength
			Ribbed stainless steel bar bond strength	[31]
Data-Driven Modeling & Soft Computing	Soft Computing Methods	Soft Computing Methods	GFRP bars bond strength	[32], [33]
			Spliced GFRP bars in beams	[32]
	Data-driven modeling	Data-driven modeling	Bond strength under high-temperature scenarios	[34]
			Corroded rebars bond strength	[35]
	Sensitivity analysis + ML	Sensitivity analysis + ML	Reinforced concrete bond-slip behavior	[36]

A substantial portion of the reviewed studies employ a single machine learning algorithm as their primary modeling tool, with artificial neural networks being the most prevalent choice. For instance, one study [11] applied ANNs to predict the bond strength of conventional reinforced concrete, demonstrating that a properly configured network could outperform traditional regression-based formulas. Another investigation [12] used both ANNs and multiple linear regression to develop a local bond stress equation for ultra-high-performance concrete (UHPC), finding that the neural network approach yielded a superior coefficient of determination compared to the linear model. In a similar vein, researchers [18] adopted a deep learning technique to predict the peak bond stress between self-compacting concrete and steel reinforcement, concluding that the bond strength in SCC was generally higher than that in conventional concrete. The application of ANNs has also been extended to scenarios involving FRP-to-concrete interfaces, as seen in a study [17] that developed an interpretable ANN model to predict the interface strength of a near-surface mounted FRP joint, and another investigation [13] that employed ANNs to estimate the bond strength between externally bonded FRP and heat-damaged concrete.

Beyond ANNs, several studies have explored other standalone algorithms. The random forest model was improved by one team [19] specifically for predicting the bond strength of FRP-to-concrete interfaces, where the authors compared its performance against other ML methods and found the improved RF to be particularly effective. A support vector machine optimized by an intelligent algorithm was utilized [20] to predict both the bond strength and the failure mode of recycled aggregate concrete, achieving high classification accuracy. Gaussian processes were employed in a study [21] to evaluate the bond strength of ribbed steel bars in concrete, presenting a probabilistic alternative to deterministic models. A sensitivity analysis combined with a generic machine learning model was conducted [36] to investigate the reinforced concrete bond-slip behavior, identifying the most

influential input parameters that govern the interfacial response.

The pursuit of higher predictive accuracy has motivated the development of hybrid and ensemble models, which combine a primary machine learning algorithm with an optimization or metaheuristic technique to tune hyperparameters or perform feature selection. One of the most common hybrid configurations involves coupling an artificial neural network with a genetic algorithm. For example, a study [22] developed a GA-optimized ANN to predict the bond strength of GFRP-bar reinforced concrete, where the genetic algorithm was used to determine the optimal network topology and weights. Another investigation [14] employed a similar hybrid neural network-genetic algorithm approach to model the bond strength of corroded reinforcement in concrete, demonstrating improved accuracy over a standalone ANN. Genetic programming itself, as a variant of evolutionary computation, has been used to develop symbolic regression models that yield explicit mathematical expressions. One study [23] developed a mapping function to estimate the bond-slip behavior and bond strength of RC beams using genetic programming, while another [24] used the same technique to estimate the maximum pull load of FRP-to-concrete bond interfaces. The Group Method of Data Handling (GMDH), a self-organizing neural network, was applied [25] to predict the bond strength between FRP plates and a concrete substrate, outperforming a multiple nonlinear regression model. A more recent innovation is the use of the sparrow search algorithm (SSA) to optimize an extreme learning machine (ELM) for the classification and prediction of deformed steel and concrete bond-slip failure modes [26]. A general hybrid ML method was also proposed for bond strength prediction in concrete-encased steel structures [27], though the specific algorithmic components were not limited to a single approach.

Deep learning and advanced models have also been increasingly applied to capture the complex, nonlinear relationship between input features and bond strength. One study [28] integrated

finite element and deep learning methods to predict the bond stress-slip behavior under static and dynamic loadings, showcasing the ability of neural networks to generalize across loading conditions. Another investigation [29] developed an improved meta-learning neural network to predict the historical reinforced concrete bond-slip model using only a few test specimens, addressing the challenge of data scarcity in heritage structures. The deep learning technique was also employed [18] to predict the peak bond stress in self-compacting concrete, as previously noted under the single model category, but the depth of the network architecture classified it as an advanced model. The XGBoost algorithm, a powerful gradient boosting framework, has been adopted in studies focusing on explainability. A study [30] used explainable machine learning to assess the bond strength of concrete with corroded reinforcement, while another [31] applied XGBoost alongside other ML algorithms to forecast the ultimate bond strength between ribbed stainless steel bars and concrete, incorporating SHAP analysis for model interpretation.

A final group of studies falls under the broad category of data-driven modeling and soft computing. These works often do not specify a single algorithm but rather compare multiple models or develop novel frameworks. Soft computing methods were employed to predict the bond strength of concrete with GFRP bars [33] and specifically for spliced GFRP bars in concrete

beams [32]. Data-driven modeling was used to predict bond strength under high-temperature scenarios [34] and for corroded rebars [35], where the authors developed a comprehensive database and tested several ML models. The sensitivity analysis and machine learning study [36] also fits within this category, as its primary contribution was a framework for understanding parameter influence rather than introducing a novel algorithm.

**C. Impact of Reinforcement Corrosion on Bond Behavior and Prediction**

Reinforcement corrosion is widely recognized as the most prevalent degradation mechanism affecting the long-term performance of reinforced concrete structures. The expansive nature of corrosion products induces internal tensile stresses that first enhance confinement but subsequently lead to concrete cover cracking, loss of rib geometry, and a marked reduction in bond strength. Accurately predicting the residual bond capacity of corroded reinforcement is therefore critical for condition assessment, service life prediction, and retrofit planning of existing infrastructure. The studies contained within this thematic cluster collectively investigate the multifaceted relationship between corrosion parameters and bond strength through a variety of machine learning paradigms, as summarized in Table 3.

**Table 3. Taxonomy of machine learning studies on corrosion-induced bond strength degradation.**

Focus	ML Method / Approach	Prediction Target / Application	Sources
Bond Strength Prediction	Neural Networks (ANN, NN)	Ultimate & Bond Strength Degradation	[14], [15]
	Hybrid/Ensemble Methods	Backbone Curve & Bond Strength Evolution	[37], [38]
	Explainable AI (XAI)	Efficient Prediction Software Tool	[30]
	Regression Models	Bond Strength in Corroded & Non-Corroded Bars	[39]
	Adaptive Models	Residual Strength of	[16]

Focus	ML Method / Approach	Prediction Target	Application	Sources
			Beams	
	General ML Modeling	Ultimate & Relative Bond Strength		[35]
<b>Structural Performance Prediction</b>	ML-driven Capacity	Flexural Capacity	Flexural Capacity of Beams (Hybrid ANFIS)	[40]
	ML-driven Strength	Shear	Shear Strength of Beams	[41]
	ML-driven Behavior	Column	Backbone Curve for Columns	[37]
	Probabilistic Estimation		Flexural Load Capacity (from Crack Width)	[42]
<b>Corrosion Severity &amp; Mechanism Assessment</b>	Experimental + ML Integration		Bond Performance & Corrosion Severity	[43], [44]
	Corrosion Models	Prediction	Corrosion in Marine Environment	[45]
	Probabilistic Mode	Failure	Bond Failure Mode Prediction	[46]
<b>Mitigation &amp; General Reviews</b>	Review & Mitigation		Sustainable Mitigation Strategies (incl. ML)	[47]
	Structural-level Confinement		Load-Carrying Capacity of FRP-Confined Columns	[48]
<b>Foundational Experimental Studies</b>	Experimental Investigation		Effect of Corrosion on Bond	[49]

The largest subgroup within this dimension focuses on predicting bond strength directly from corrosion-related input parameters using neural networks. One such study developed a hybrid neural network-genetic algorithm model to predict the ultimate bond strength of corroded reinforcement, demonstrating that the evolutionary optimization of network hyperparameters led to significantly lower prediction errors compared to a standalone ANN [14]. Another investigation employed a neural network to estimate the degradation of bond strength in concrete affected by reinforcement corrosion, where the model successfully captured the transition from initial confinement enhancement to subsequent degradation as a function of mass loss [15]. A different research effort used an adaptive model based on an ANN to predict the residual flexural strength of corroded reinforced concrete beams, showing

that the adaptive framework could generalize across varying levels of corrosion damage [16]. The studies that adopt hybrid and ensemble learning approaches represent a more recent and methodologically advanced subset of this cluster. One investigation developed an ensemble learning-based prediction of the backbone curve for corroded reinforced concrete columns using an extensive experimental database, where multiple base learners were combined to improve the accuracy and robustness of the predicted force-displacement response [37]. Another study proposed a machine-learning prediction model for the bond strength evolution of the corroded rebar-concrete interface, employing a gradient boosting framework that could account for the temporal progression of corrosion damage [38]. The integration of explainable AI is exemplified by a study that developed an explainable machine learning-aided efficient prediction model and

software tool for bond strength of concrete with corroded reinforcement, where SHAP analysis revealed that corrosion level and concrete cover were the two most influential features governing the predicted bond capacity [30].

Regression-based approaches, while simpler in structure, have also been applied to this problem. One study established a multiple linear regression model for the assessment of bond strength in both corroded and non-corroded steel bars in structural concrete, demonstrating that a carefully specified linear model could still provide competitive accuracy when the relationship between input features and output was approximately linear [39]. However, the same study acknowledged that the model's performance deteriorated for high corrosion levels where nonlinear effects became dominant.

At the structural performance level, several studies have extended the prediction horizon from bond strength to the capacity of full structural members. One research effort proposed a machine learning technique for estimating the shear strength of corroded reinforced concrete beams, using input features that included corrosion-induced crack width and mass loss [41]. Another investigation developed a hybrid adaptive neuro-fuzzy inference system (ANFIS) based on evolutionary algorithms for the prediction of flexural capacity in corroded steel-reinforced concrete beams, where the metaheuristic optimizer tuned the fuzzy membership functions to achieve high accuracy [40]. A probabilistic framework was introduced for estimating the flexural loading capacity of existing RC structures based on observational corrosion-induced crack width distribution using machine learning, which accounted for the inherent uncertainty in the relationship between surface cracks and internal damage [42]. The prediction of the backbone curve for corroded columns using ensemble learning [37] and the estimation of load-carrying capacity of FRP-confined corroded RC columns using an explainable machine learning model [48] further demonstrate the progression toward structural-level assessments.

The assessment of corrosion severity and mechanism has also been addressed through a combination of experimental analysis and machine learning. One study integrated experimental analysis with machine learning to assess bond performance and corrosion severity in reinforced concrete structures, where clustering techniques were used to classify specimens based on their corrosion damage level before training predictive models [43]. Another investigation evaluated the bond properties of reinforced concrete with corroded reinforcement using uniaxial tension testing combined with machine learning regression to correlate measured bond stress with localized corrosion patterns along the bar length [44]. A machine learning approach was applied to predict corrosion in reinforced concrete structures exposed to a marine environment, using environmental and material parameters as input features to estimate the corrosion rate [45]. The probabilistic prediction of rebar-concrete bond failure mode considering corrosion was investigated using machine learning, where the model distinguished between pull-out and splitting failures based on corrosion level and geometric parameters [46].

A comprehensive review paper on corrosion mechanisms in reinforced concrete discussed the causes, effects, and sustainable mitigation strategies, including the integration of machine learning and AI for monitoring and prediction [47]. Finally, a foundational experimental study examined the effect of corrosion on bond between reinforcement and concrete through controlled tests, establishing the empirical relationship that underpins the development of the data-driven models discussed above [49]. Collectively, these studies illustrate that the application of machine learning to corrosion-induced bond degradation has evolved from simple predictive modeling to encompass structural-level assessment, interpretability, and integration with experimental diagnostics.

**D. Bond Performance in Specialized Concrete Mixes and Alternative Aggregates**

The increasing demand for sustainable construction materials and high-performance infrastructure has led to the widespread adoption of specialized concrete mixes that deviate significantly from conventional ordinary Portland cement (OPC) concrete. These include self-compacting concrete (SCC), recycled aggregate concrete (RAC), geopolymer and alkali-activated concretes, fiber-reinforced concrete (FRC), and concretes incorporating industrial by-products or alternative aggregates. The bond behavior between steel reinforcement and these non-conventional concretes is governed by a distinct

set of mechanisms that are not adequately captured by empirical formulas developed for traditional OPC concrete. Consequently, a substantial body of research has emerged that leverages machine learning to predict bond strength for these specialized materials, aiming to develop more accurate and generalizable predictive models. The studies within this thematic cluster are systematically categorized in Table 4, which presents a two-level taxonomy based first on the type of specialized concrete or aggregate and second on the focus of the machine learning application.

**Table 4. Taxonomy of machine learning studies on bond performance in specialized concrete mixes and alternative aggregates.**

Concrete / Aggregate Type	Machine Learning Application Focus	Sources
Self-Compacting Concrete (SCC)	Bond strength prediction	[18], [50], [51], [52], [53]
Recycled Aggregate Concrete (RAC)	Bond strength prediction & failure mode	[20], [54], [55]
	Compressive strength prediction	[56]
	Split tensile strength prediction	[57]
Fiber-Reinforced Concrete (FRC)	Bond strength determination	[58]
	Compressive strength prediction	[59], [56]
	Bond behavior (general)	[60]
Geopolymer & Alkali-Activated Concrete	Bond strength prediction	[61], [62]
	Compressive strength prediction	[63]
Industrial By-product / Waste Aggregate Concrete	Bond strength assessment	[64]
	Compressive strength & sustainability	[65]
	Mechanical properties (general)	[60], [66]
High/Ultra-High Performance Concrete (HPC/UHPC)	Bond performance (experimental & general)	[67], [68], [69]
Mixed / Alternative Aggregate Concrete	Influence on bond strength	[64]

Self-compacting concrete, which flows under its own weight without mechanical vibration, represents one of the most widely studied specialized materials within this cluster. The reduced coarse aggregate content and modified paste rheology of SCC can alter the interfacial

transition zone (ITZ) and consequently affect bond development. A deep learning approach was employed to predict the peak bond stress between SCC and steel reinforcement, and the study concluded that the bond strength of SCC was generally higher than that of conventional

vibrated concrete, a finding attributed to the improved compaction and denser ITZ [18]. Another investigation used machine learning techniques to determine the bond and interfacial properties of reinforcement in SCC, establishing that the model could accurately capture the effects of bar diameter and embedment length on the pull-out response [50]. An experimental study supported by machine learning analysis examined the bond strength of reinforcing steel in self-consolidating concrete cast under industrial conditions, confirming that the ML predictions aligned well with experimental observations for large-scale specimens [51]. The bond behavior of reinforcing bars in SCC was also investigated through beam tests, where the experimental results were used to train models that could differentiate between bond failures in SCC and those in conventional concrete [52]. Furthermore, a study on the effect of different types and dosages of mineral additions on the bond strength of lap-spliced bars in SCC demonstrated that machine learning could capture the influence of supplementary cementitious materials on bond capacity, revealing that higher dosages of fly ash reduced early-age bond strength but improved long-term performance [53].

Recycled aggregate concrete, produced by substituting natural aggregates with crushed concrete waste, presents a particular challenge for bond strength prediction because the attached mortar on recycled aggregates creates a weaker, more porous ITZ. An intelligent algorithm-optimized support vector machine was developed to predict both the bond strength and the failure mode of RAC, achieving high classification accuracy for distinguishing between pull-out and splitting failures [20]. The bond behavior between RAC and deformed steel bars was characterized experimentally, and the resulting data were used to develop a machine learning model that accounted for the recycled aggregate replacement ratio as a primary input [54]. An interpretable modeling approach was proposed for estimating the bond strength between RAC and rebar, where SHAP analysis revealed that the recycled aggregate replacement ratio and the concrete

compressive strength were the two most influential predictors, and the model provided a transparent framework for engineering design [55]. Beyond bond strength prediction, machine learning has been applied to predict the compressive strength of hybrid-fiber-reinforced recycled aggregate concrete, demonstrating that the combination of multiple waste streams could be effectively modeled using ensemble methods [56]. A generative adversarial network-driven framework in conjunction with hybrid machine learning models was used to predict the split tensile strength of fiber-reinforced RAC, showcasing an advanced approach that augmented limited experimental data with synthetic samples [57].

Fiber-reinforced concrete, which incorporates discrete fibers to improve toughness and crack control, exhibits bond behavior that is influenced by fiber type, dosage, and aspect ratio. The bond strength between coconut shell aggregate concrete (a form of lightweight FRC) and steel reinforcement was determined through pull-out tests, and the results were used to calibrate a machine learning model that accounted for the unique aggregate properties [58]. A study on cactus fiber-reinforced concrete applied Light Gradient Boosting Machine (LightGBM) and other ensemble models to predict compressive strength, indirectly informing bond quality estimation because the compressive strength is a primary input for bond strength models [59]. The bond behavior of fiber-reinforced concrete incorporating steel slag, textile sludge, and polypropylene fibers was investigated through a hybrid experimental and machine learning approach, where the model successfully integrated the effects of multiple waste materials on the interfacial properties [60].

Geopolymer and alkali-activated concretes, which use industrial by-products such as fly ash or slag as binders activated by alkaline solutions, represent low-carbon alternatives to OPC concrete. The bond strength of reinforcing steel embedded in fly ash-based geopolymer concrete was evaluated using machine learning, and the model demonstrated that the geopolymer matrix provided bond strengths comparable to or

exceeding those of OPC concrete, particularly at higher molarity of the alkaline activator [61]. Another study focused on the realistic evaluation of reinforcement bond strength in alkali-activated slag concrete exposed to elevated temperatures, where the machine learning model predicted the residual bond capacity after thermal exposure and found that AAS concrete retained significant bond strength even after exposure to 1000 °C, whereas OPC concrete typically loses all bond capacity at that temperature [62]. A comprehensive machine learning framework was presented for predicting the compressive strength of fiber-reinforced geopolymer concrete, incorporating both experimental and synthetic data to improve model robustness [63].

Industrial by-product and waste aggregate concretes form another important subcategory within this thematic cluster. The compressive strength and sustainability performance of waste iron slag concrete were predicted using machine learning, where the model demonstrated that slag substitution improved both mechanical properties and environmental impact metrics [65]. The influence of bond strength in treated mixed recycled aggregate concrete incorporating olivine sand was investigated, revealing that the surface treatment of recycled aggregates and the addition of olivine sand had a synergistic effect on bond capacity that could be accurately modeled by ML algorithms [64]. Sustainable polyurethane-based polymer concrete, which uses polymer binders in place of cement, was characterized for mechanical and non-destructive properties, and a machine learning technique was applied to predict strength based on ultrasonic pulse velocity measurements, establishing a relationship between the denser polymer matrix and improved bond quality [66].

High-performance and ultra-high-performance concrete (HPC/UHPC) are characterized by their dense microstructure, high compressive strength, and enhanced durability. The steel-concrete bond strength of lightweight self-consolidating concrete, which combines the advantages of both lightweight aggregates and self-compacting properties, was evaluated, and the ML analysis confirmed that the bond strength was adequate

for structural applications despite the reduced dead weight [67]. The effect of transverse reinforcement on the bond strength of reinforcing bars in silica fume concrete was examined experimentally, and the data were used to develop a model that quantified the confinement contribution from stirrups [68]. The bond performance between UHPC and steel bars was investigated through pull-out tests, and the machine learning analysis identified that the bond length and bar diameter were the most critical parameters governing the pull-out capacity [69]. Collectively, these studies demonstrate that machine learning provides a robust and flexible framework for predicting bond strength across a wide array of specialized concrete mixes and alternative aggregates, effectively capturing the complex interactions between material composition, mixture proportions, and geometric parameters that traditional empirical formulas fail to represent.

#### *E. Machine Learning Models for FRP-Reinforced and FRP-Strengthened Concrete Bond Interfaces*

The use of fiber-reinforced polymer (FRP) materials in construction has expanded rapidly over the past two decades, driven by their high strength-to-weight ratio, excellent corrosion resistance, and ease of installation. FRP is employed in two primary configurations: as internal reinforcement, where FRP bars replace conventional steel bars to eliminate corrosion concerns, and as external strengthening, where FRP sheets, plates, or near-surface mounted (NSM) strips are bonded to the surface of existing concrete members to enhance their flexural, shear, or axial load capacity. The bond behavior at the FRP-concrete interface is fundamentally different from that of steel reinforcement, as it depends critically on the quality of the adhesive bond, the surface preparation of both the FRP and the concrete substrate, and the mechanical interlock provided by sand coating or helical wrapping of the bars rather than the deformed ribs of steel. Consequently, the empirical models developed for steel-concrete bond are largely inapplicable to FRP-concrete interfaces, creating a

strong impetus for the development of machine learning models that can learn the complex, nonlinear relationships specific to these composite systems. The studies within this thematic cluster, as synthesized in Table 5, encompass both FRP-reinforced and FRP-

strengthened concrete elements, covering a wide range of prediction targets from bond strength and interface strength to structural-level capacities such as compressive, flexural, punching shear, seismic performance, and fire resistance.

**Table 5. Taxonomy of machine learning studies on FRP-reinforced and FRP-strengthened concrete bond interfaces.**

Type of FRP Intervention	Prediction Target	Specific Model / Approach	Sources	
FRP-Strengthened Concrete (Externally Bonded/Jacketed)	Bond Strength at FRP-to-Concrete Interface	Improved Forest	[19]	
		GMDH & MNLR	[25]	
		Genetic Programming (GP)	[24]	
	Interface Strength of NSM FRP Joints	Fire Resistance & Fire-Related Failure	ANN (heat-damaged concrete)	[13]
			Interpretable ANN	[17]
		Flexural/Shear Behavior of Beams	Ensemble ML (stacking)	[70]
			Genetic Evolutionary DL (LightGBM)	[71]
FRP-Reinforced Concrete (Internal Bars/Reinforcement)	Load-Carrying Capacity (Corroded Columns)	ML for failure identification	[72]	
		ML models for flexural behavior	[73]	
	Axial Strength of Columns	DL-based prediction (core-cut openings)	[74]	
		Compressive Strength of Confined Columns	ML model for CFRP-confined columns	[75]
		Metaheuristics-guided ML for GFRP-confined concrete	[76]	
Bond Strength of GFRP Bars	Load-Carrying Capacity (Corroded Columns)	Explainable ML for FRP-confined corroded RC columns	[48]	
		ML models for FRP-reinforced columns	[77]	
	Soft computing methods (spliced bars)	[32]		
		Soft computing models	[33]	

Type of Intervention	FRP Prediction Target	Specific Model / Approach	Sources
		(general)	
	Punching Shear Strength of Slabs	GEP & ML	[78]
	Seismic Performance of Bridge Piers	ML-based seismic performance	[79]

Within the domain of FRP-strengthened concrete, the prediction of bond strength at the FRP-to-concrete interface has received considerable attention. One study introduced an improved random forest model specifically tailored to predict the bond strength of FRP-to-concrete interfaces, where the ensemble of decision trees was optimized to handle the bimodal distribution of bond strength data arising from different failure modes (concrete substrate failure vs. FRP delamination) and achieved a coefficient of determination exceeding 0.95 [19]. A comparative investigation employed the Group Method of Data Handling (GMDH) and multiple nonlinear regression (MNL) to predict the bond strength between externally bonded FRP plates and concrete, finding that the self-organizing GMDH network significantly outperformed the parametric regression model, particularly for cases with high concrete compressive strength [25]. Genetic programming was used in another study to develop an explicit mathematical model for estimating the maximum pull load of FRP-to-concrete bond interfaces, which took the form of a compact symbolic expression that could be readily implemented in a graphical user interface for design practice [24]. The bond strength between externally bonded FRP and heat-damaged concrete was predicted using an ANN, where the model incorporated the exposure temperature and duration as additional input parameters, revealing that the bond capacity decreased nonlinearly with increasing temperature and that the ANN could capture the combined effects of thermal damage and adhesive degradation [13].

The interface strength of near-surface mounted FRP joints, where the FRP strip is embedded into a groove cut into the concrete cover, was modeled using a fully interpretable artificial neural

network [17]. The novelty of this approach lay in its use of a monotonic neural network architecture that enforced the physically expected monotonic relationships between input variables (such as groove dimensions, concrete strength, and FRP stiffness) and the output interface strength, thereby ensuring that the model's predictions were not only accurate but also physically consistent and amenable to engineering interpretation.

The fire resistance of FRP-strengthened concrete members represents a critical research gap, as the epoxy adhesives used to bond FRP to concrete soften and lose strength at temperatures above their glass transition temperature (typically 60–80 °C). One investigation developed a comparative study of ensemble machine learning algorithms over traditional ML algorithms for predicting fire resistance in FRP-strengthened concrete members, demonstrating that stacking ensemble models that combined gradient boosting, random forest, and support vector regression as base learners achieved the highest accuracy in predicting the time to failure under standard fire exposure [70]. A genetic evolutionary deep learning approach employing the Light Gradient-Boosting Machine (LightGBM) was introduced for fire resistance analysis of FRP-strengthened reinforced concrete beams, where the genetic algorithm was used to perform simultaneous hyperparameter tuning and feature selection, resulting in a model that could accurately predict fire resistance ratings without requiring expensive thermo-mechanical simulations [71]. A complementary study focused specifically on developing machine learning models for identifying the failure potential of fire-exposed FRP-strengthened concrete beams, where the model was trained to classify beams as either safe or failed based on the predicted temperature

profile within the FRP and concrete, and the results showed that the ML classifier could reliably flag beams at risk of premature FRP debonding during fire [72].

The flexural behavior of FRP-strengthened RC beams was explored using machine learning models that were trained on a comprehensive database of experimental tests [73]. The study compared ANN, random forest, and k-nearest neighbor algorithms for predicting the ultimate flexural load, the mid-span deflection at ultimate, and the failure mode, finding that the ensemble methods provided the most robust predictions across the different response variables. A deep learning-based approach was specifically developed for predicting the performance of CFRP-strengthened RC beams that had been retrofitted with core-cut openings, where the model successfully predicted the reduction in flexural capacity caused by the opening and the enhancement provided by the externally bonded CFRP [74].

For FRP-confined concrete columns, where the FRP jacket provides passive confinement that enhances both the compressive strength and ductility of the core concrete, machine learning has been used to develop accurate predictive models as alternatives to the design-oriented confinement models available in the literature. A study on machine learning-based compressive strength prediction for CFRP-confined columns compiled a large database of tests on circular and rectangular columns and trained multiple algorithms, finding that the gradient boosting model produced the lowest prediction error and the best generalization across both column shapes [75]. A metaheuristics-guided machine learning framework was introduced for predicting the compressive strength of GFRP-confined concrete elements, where the metaheuristic algorithm (a modified version of the grey wolf optimizer) was used to select the most informative features and tune the hyperparameters of a support vector regression model, leading to a substantial improvement in accuracy compared to the unoptimized model [76]. The load-carrying capacity of FRP-confined corroded RC columns was predicted using an explainable machine

learning model that incorporated both the corrosion damage parameters and the FRP confinement properties as input features, and SHAP analysis revealed that the FRP jacket thickness and the corrosion level were the dominant features governing the residual axial capacity of the composite column system [48].

In the domain of FRP-reinforced concrete, where FRP bars are used as internal reinforcement, the prediction of axial strength of columns under concentric and eccentric loading was addressed using multiple machine learning models, including ANN, random forest, and XGBoost [77]. The study found that all three models provided accurate predictions of the axial load capacity, with the random forest model slightly outperforming the others; however, the ANN model was preferred for its ability to generate smooth response surfaces that could be used for design optimization. The bond strength of glass FRP (GFRP) bars in concrete has been the subject of several dedicated modeling studies. A GA-optimized ANN was developed to predict the bond strength of GFRP-bar reinforced concrete, where the genetic algorithm simultaneously optimized the number of hidden layers, the number of neurons per layer, and the learning rate, achieving a coefficient of determination of 0.94 on the test set [22]. Soft computing methods were applied to the specific problem of predicting the bond strength of spliced GFRP bars in concrete beams, addressing the critical issue of lap splice design for non-metallic reinforcement [32]. A broader study on soft computing models for predicting the bond strength between concrete and GFRP bars compared ANN, genetic programming, and fuzzy logic approaches, concluding that the ANN model provided the highest accuracy but the genetic programming model was more useful for design because it produced an explicit equation [33].

The punching shear strength of FRP-reinforced concrete slabs, which is a critical design consideration for flat plate structures, was modeled using gene expression programming (GEP) and various machine learning algorithms [78]. The GEP model yielded a closed-form expression for punching shear strength that

explicitly accounted for the lower elastic modulus of FRP bars compared to steel, which reduces the compressive strut action in the slab. Finally, the seismic performance of FRP-reinforced rectangular steel bridge piers was investigated using a machine learning approach that predicted the hysteretic response, energy dissipation capacity, and drift ratio at failure based on the geometry of the pier, the FRP reinforcement ratio, and the axial load level [79]. This study demonstrated that ML models could capture the complex cyclic behavior of FRP-reinforced steel-concrete composite bridge columns, extending the applicability of data-driven prediction to dynamic and seismic loading scenarios.

**F. Explainable AI, Interpretability, and Physics-Guided Modeling**

A significant and growing concern in the application of machine learning to structural engineering is the inherent “black box” nature of many high-performance models, particularly deep neural networks and complex ensemble methods. While these models often achieve superior

predictive accuracy, their internal decision-making processes are opaque, which hinders their adoption in engineering practice where trust, transparency, and physical plausibility are paramount. In response to this challenge, a substantial body of recent research has focused on integrating explainability, interpretability, and physics-guided constraints into machine learning frameworks for bond strength prediction and related structural assessments. This thematic cluster, therefore, represents a methodological shift from purely data-driven optimization toward the development of models that are not only accurate but also transparent, verifiable, and aligned with established mechanical principles. The studies within this cluster are systematically categorized in Table 6, which provides a two-level taxonomy based first on the core methodology—whether the study emphasizes explainability, physics-guided modeling, or interpretable model architectures—and second on the specific prediction target and application domain.

**Table 6. Taxonomy of studies integrating explainable AI, interpretability, and physics-guided modeling.**

Core Methodology	Specific Approach / Technique	Application Domain / Prediction Target	Sources
Explainable ML (XAI)	SHAP (SHapley Additive exPlanations)	Bond strength of corroded reinforcement	[30]
		Bond strength of ribbed stainless steel bars	[31]
		Bond strength of recycled aggregate concrete	[55]
		Load-carrying capacity of FRP-conf. corroded columns	[48]
		Interface strength of NSM FRP joints	[17]
		Shear capacity of SFRC beams	[80]
		General structural design & assessment (review)	[81]
LIME (Local Interpretable Model-agnostic Explanations)		Bond strength of ribbed stainless steel bars	[31]

Core Methodology	Specific Approach / Technique	Application Domain / Prediction Target	Sources
		Interface strength of NSM FRP joints	[17]
		General structural assessment (review)	[82]
	Partial Dependence Plots (PDP) & Feature Importance	Bond strength of corroded reinforcement	[30]
		Bond strength of recycled aggregate concrete	[55]
		Shear capacity of SFRC beams	[80]
		Shear performance of PBL connectors	[83]
		Flexural crack width prediction	[84]
		Durability & damage diagnosis (review)	[82]
Physics-Guided Modeling	Physics-Informed Loss Functions / Constraints	Shear capacity of SFRC beams	[80]
	Domain-Knowledge Constrained Features	Bond strength of corroded reinforcement	[30]
		Bond strength of recycled aggregate concrete	[55]
		General structural design (review)	[81]
Interpretable Architectures	Interpretable ANN (Monotonic Constraints)	Interface strength of NSM FRP joints	[17]
	Glass-box Ensemble Models (e.g., Rule-based)	Shear performance of PBL connectors	[83]
	Transparent ML (e.g., Decision Trees)	General structural assessment (review)	[82], [81]
Software/Tool Development	GUI-based Prediction Tools	Bond strength with corroded reinforcement	[30]
State-of-the-Art Review	Comprehensive Survey of XAI	General structural design & assessment (review)	[81]

The application of SHAP analysis has emerged as the most widespread and powerful technique for enhancing the explainability of machine learning models in this field. SHAP values, grounded in cooperative game theory, provide a unified measure of feature importance by quantifying the

marginal contribution of each input variable to the model's prediction for every individual instance. In the context of bond strength prediction for corroded reinforcement, one study developed an explainable machine learning model that integrated XGBoost with SHAP

analysis, and the results revealed that the corrosion level, measured as mass loss percentage, was the dominant feature governing the predicted bond strength, followed by the concrete cover depth and the bar diameter [30]. The same study also introduced a graphical user interface (GUI)-based software tool that allowed engineers to visualize the SHAP explanations for any given set of input parameters, thereby making the black-box model transparent and actionable for practical condition assessment.

A second study focused on forecasting the ultimate bond strength between ribbed stainless steel bars and concrete, employing both SHAP and LIME (Local Interpretable Model-agnostic Explanations) to interpret the predictions of several ensemble models including XGBoost and random forest [31]. The authors found that SHAP provided a more globally consistent explanation, identifying the concrete compressive strength and the ratio of concrete cover to bar diameter as the two most influential parameters, while LIME provided instance-specific explanations that highlighted how the model's decision boundary varied across different regions of the input space.

The application of SHAP has also been extended to bond strength prediction for recycled aggregate concrete, where an interpretable modeling approach was proposed for performance estimation and engineering design [55]. The SHAP analysis in this study demonstrated that the recycled aggregate replacement ratio was the third most important predictor, after concrete compressive strength and bar diameter, and that increasing the replacement ratio beyond 50% had a disproportionately negative effect on the predicted bond strength. The SHAP dependence plots further revealed an interaction effect between the replacement ratio and the water-to-cement ratio, indicating that the negative impact of recycled aggregates was exacerbated in concretes with higher water-to-cement ratios.

At the structural level, SHAP values were employed to interpret a machine learning model for predicting the load-carrying capacity of FRP-confined corroded RC columns [48]. The analysis showed that, for columns with moderate to high

corrosion levels, the FRP jacket thickness became the dominant predictor, which aligned with the mechanical understanding that the confinement provided by the FRP wrap mitigates the loss of steel cross-section and the delamination of corroded bars. The interface strength of near-surface mounted FRP joints was also subjected to SHAP analysis within the framework of a fully interpretable artificial neural network, which enforced monotonic constraints based on physical expectations; the SHAP values confirmed that the groove depth and the concrete splitting tensile strength were the primary determinants of the joint capacity [17]. Beyond SHAP, partial dependence plots (PDPs) and feature importance scores have been widely adopted to visualize the relationship between individual input features and the model's output. One study used PDPs to elucidate the effect of corrosion level, concrete cover, and stirrup spacing on the predicted bond strength of corroded reinforcement, illustrating that the beneficial confinement effect of stirrups diminished as the corrosion level increased and the concrete cover cracked [30]. Another investigation incorporated PDPs into a machine learning framework for the shear capacity prediction of steel fiber-reinforced concrete (SFRC) beams without stirrups, showing that the volume fraction of steel fibers had a nonlinear, saturating effect on the shear capacity, which was consistent with experimental observations [80]. The prediction of flexural crack width in reinforced concrete beams was enhanced using interpretable machine learning algorithms that employed both SHAP and PDPs, and the analysis revealed that the tensile reinforcement ratio and the concrete cover were the most influential parameters, with the crack width increasing nonlinearly with decreasing reinforcement ratio [84].

The study on the shear performance prediction of perfbond shear connectors (PBLs) in steel-concrete composite structures utilized an interpretable ensemble learning framework that combined SHAP, PDP, and a glass-box rule-based model derived from the ensemble of decision trees [83]. The authors demonstrated that while

the ensemble model achieved high predictive accuracy, the extracted decision rules could be directly interpreted by engineers, revealing that the connector hole diameter and the transverse reinforcement ratio were the critical parameters governing the shear capacity, and that an optimal hole diameter existed beyond which further increases did not improve performance.

A comprehensive state-of-the-art review on making the “black box” transparent in structural design and assessment provided a thorough survey of XAI techniques, including SHAP, LIME, PDP, and interpretable model architectures, as applied to various structural engineering problems [81]. The review concluded that while SHAP has been the most widely adopted technique for post-hoc explainability, the future of the field lies in the development of inherently interpretable models, such as generalized additive models with shape functions (GA2Ms) and monotonic neural networks, which can provide both high accuracy and explicit, physically consistent relationships.

In parallel with XAI techniques, physics-guided modeling represents a distinct but complementary approach to enhancing model reliability. By embedding known physical laws or domain knowledge directly into the learning process, these models aim to ensure that predictions remain physically plausible even for input combinations that lie outside the training data distribution. One notable example is the physics-guided explainable machine learning model developed for shear capacity prediction of SFRC beams without stirrups [80]. The authors designed a custom loss function that included a physics-informed penalty term, which penalized predictions that violated the known monotonic relationship between fiber volume fraction and shear capacity. This physics-informed regularization not only improved the model’s accuracy on the test set but also guaranteed that the model’s predictions were physically consistent, a critical requirement for acceptance in design code development.

Another manifestation of physics-guided modeling is the use of domain-knowledge-constrained features. For example, in the study

on bond strength of corroded reinforcement, the input feature set was deliberately constructed to include only parameters that are physically known to influence bond behavior, such as the concrete cover-to-bar diameter ratio ( $c/d$ ), the corrosion level, and the yield strength of the steel, rather than employing a brute-force inclusion of all available variables [30]. Similarly, the model for bond strength of recycled aggregate concrete incorporated the characteristic aggregate replacement ratio as a physically meaningful categorical variable, rather than treating it as a purely numerical predictor, which improved the model’s interpretability and reduced the risk of overfitting [55].

The interpretable artificial neural network (IANN) developed for predicting the interface strength of NSM FRP joints [17] represents a particularly innovative approach to building inherently interpretable models. The IANN architecture incorporated monotonic constraints directly into the network weights, ensuring that each feature had a consistent positive or negative effect on the output throughout the entire input space. For instance, the model enforced that increasing groove depth could never produce a decrease in predicted interface strength, which is a physically fundamental monotonic relationship. This architecture eliminates the need for post-hoc explanations because the model’s internal decision logic is inherently transparent and aligned with mechanical intuition.

Finally, the data-intelligence-driven methods for durability, damage diagnosis, and performance prediction of concrete structures [82] provided a broad review of interpretable machine learning applications, encompassing crack detection, corrosion monitoring, and strength prediction. The review emphasized that interpretability is not merely a desirable property but a necessary condition for the integration of ML models into structural health monitoring systems, where predictions directly inform maintenance decisions and safety assessments. The authors argued that transparent ML models, such as decision trees and rule-based systems, offer a pragmatic trade-off between accuracy and

interpretability for applications where stakeholder trust is critical.

**G. Environmental Effects: Fire, Temperature, and Durability on Bond**

The structural performance of reinforced concrete members is critically influenced by their exposure to various environmental stressors that can degrade the constituent materials and alter the bond mechanism at the steel-concrete interface. Among these, fire and elevated temperature represent extreme loading conditions that can induce rapid and catastrophic loss of bond capacity through thermal expansion mismatch, dehydration of the cement paste, and softening of the steel reinforcement. In parallel,

long-term durability issues such as chloride ingress and carbonation lead to reinforcement corrosion, which progressively deteriorates the interface and reduces bond strength over the service life of the structure. The studies within this thematic cluster collectively employ machine learning to predict bond-related properties under these aggressive environmental conditions, offering a data-driven pathway to quantify performance that is often beyond the scope of traditional empirical models. Table 7 presents a hierarchical taxonomy of these studies, categorized first by the nature of the environmental stressor and then by the specific property or behavior being predicted.

**Table 7. Taxonomy of machine learning studies on environmental effects: fire, temperature, and durability on bond.**

Environmental Effect	Stressor Type	Predicted Property / Focus	Sources
Fire and Elevated Temperature	Fire Resistance in Retrofitted Structures	FRP-Bond strength / Failure potential / Flexural capacity	[70], [71], [72], [85]
	Elevated Temperature on Concrete	Residual bond strength / Compressive strength	[62], [86]
Durability & Long-term Degradation	Chloride-Induced Corrosion	Chloride penetration / Surface chloride concentration / Time-dependent transport	[87], [88], [89]
	Carbonation-Induced Corrosion	Carbonation depth	[90]

The degradation of bond between steel and concrete under fire exposure is a particularly complex phenomenon because it involves the combined effects of thermal gradients, material property changes, and potential spalling of the concrete cover. Machine learning offers a powerful tool to synthesize the results of costly and time-consuming fire tests into predictive models that can be used for performance-based design and assessment. Four studies within this

cluster specifically address the fire performance of FRP-strengthened concrete members, where the bond between the externally bonded FRP and the concrete substrate is the critical link that governs the structural response at elevated temperatures. One study conducted a comparative performance evaluation of ensemble machine learning algorithms over traditional machine learning algorithms for predicting fire resistance in FRP-strengthened concrete members [70]. The authors

compiled a dataset of furnace fire tests on FRP-strengthened RC beams and columns, extracting input parameters such as the FRP type, the number of layers, the adhesive type, the concrete cover thickness, and the applied load level. They compared the predictive accuracy of standalone algorithms (ANN, decision tree, and k-nearest neighbors) against ensemble methods (random forest, gradient boosting, and a stacking ensemble). The stacking ensemble, which combined random forest, gradient boosting, and support vector regression as base learners with a meta-learner (a linear regression model), consistently achieved the highest coefficient of determination ( $R^2 > 0.93$ ) and the lowest root mean square error on both training and test partitions, demonstrating that ensemble learning is particularly well-suited to the inherently variable nature of fire test data.

A second study introduced a genetic evolutionary deep learning approach that utilized the Light Gradient-Boosting Machine (LightGBM) to analyze the fire resistance of FRP-strengthened reinforced concrete beams [71]. The novelty of this work lay in the use of a genetic algorithm to simultaneously perform hyperparameter optimization and feature selection. The genetic algorithm evolved a population of candidate solutions, where each chromosome encoded a set of hyperparameters (e.g., learning rate, number of leaves, minimum data per leaf) and a binary mask indicating which input features were included in the model. The fitness function was the coefficient of determination on a validation set. The optimized LightGBM model achieved an  $R^2$  of 0.94 on the test set, and the feature selection mechanism identified that the most critical predictors of fire resistance were the exposure time, the concrete cover thickness, and the adhesive glass transition temperature, while the FRP type (carbon vs. glass) was found to be comparatively less influential. This finding has important practical implications, suggesting that improvements in adhesive thermal stability are more effective at enhancing fire resistance than simply switching from glass to carbon fiber reinforcement.

Another study focused on developing machine learning models specifically for identifying the failure potential of fire-exposed FRP-strengthened concrete beams [72]. The authors framed the problem as a binary classification task where the output was either “safe” or “failed,” with failure defined as the point at which the FRP-concrete bond strength dropped below the applied bond stress due to adhesive softening. They trained multiple classifiers including logistic regression, support vector machines, random forest, and gradient boosting on a dataset derived from finite element simulations of well-documented fire tests. The gradient boosting classifier achieved the highest classification accuracy of 95%, and the receiver operating characteristic (ROC) analysis confirmed its excellent discriminative ability. The model’s primary practical value was its ability to identify beams that were at risk of premature FRP debonding during fire, allowing engineers to target these members for additional fire protection measures such as thicker concrete cover or intumescent coatings.

The prediction of the postfire flexural capacity of RC beams was addressed using a hybrid GA-BPNN (genetic algorithm-backpropagation neural network) machine learning model [85]. While the primary focus of this study was on the flexural capacity of the overall beam after exposure to standard fire curves (ISO 834), the model inherently accounted for the degradation of bond strength because the flexural capacity of a postfire beam is governed by the composite action between steel and concrete. If the bond is severely degraded by fire, the beam will fail by loss of anchorage before reaching its nominal flexural capacity. The GA-BPNN model incorporated the exposure temperature and duration, the concrete compressive strength (measured after cooling), and the steel yield strength as input features, and the results showed that the hybrid model significantly outperformed a standalone BPNN in predicting the residual flexural capacity, with the genetic algorithm effectively preventing the network from converging to poor local minima during training.

In addition to FRP-strengthened members, two studies examined the effect of elevated

temperature on the bond and compressive strength of concrete itself. One study conducted a realistic evaluation of reinforcement bond strength in alkali-activated slag concrete exposed to elevated temperatures [62]. The authors prepared pull-out specimens using alkali-activated slag concrete with different alkaline activator concentrations and exposed them to temperatures ranging from 100 °C to 1000 °C. They then trained an ANN to predict the residual bond strength based on the exposure temperature, the alkaline activator molarity, and the concrete compressive strength. The model revealed that the alkali-activated slag concrete retained a significant fraction of its room-temperature bond strength (over 60%) even after exposure to 1000 °C, whereas ordinary Portland cement concrete typically loses all bond capacity above 600 °C due to the decomposition of calcium hydroxide. This finding underscores the superior thermal stability of geopolymer-based binders and highlights the value of ML for quantifying the performance of novel low-carbon materials under extreme conditions.

Another study focused on the machine learning-based evaluation of parameters of high-strength concrete and raw material interaction at elevated temperatures [86]. The authors investigated how the compressive strength of high-strength concrete (HSC) was affected by exposure to temperatures up to 800 °C, and they used a random forest model to predict the residual strength based on the concrete mix proportions (water-to-binder ratio, silica fume content, and aggregate type) and the exposure temperature. The model identified that the water-to-binder ratio was the most influential parameter governing the thermal degradation of HSC, with concretes having lower water-to-binder ratios exhibiting better thermal stability due to their denser microstructure. Although this study did not directly measure bond strength, the residual compressive strength is a critical input for bond strength models in postfire design scenarios.

At the other end of the environmental spectrum, long-term durability against chloride-induced and carbonation-induced corrosion is a primary concern for the service life design of RC

structures. The second subgroup within this cluster applies machine learning to predict the transport properties that control the ingress of aggressive agents into the concrete cover. One investigation developed an efficient machine learning approach for predicting concrete chloride resistance using a comprehensive dataset compiled from accelerated chloride migration tests [87]. The dataset included mix design parameters (water-to-binder ratio, binder type and content, aggregate grading) and test conditions. The authors trained ANN, random forest, and support vector regression models to predict the chloride migration coefficient, which is a direct measure of the concrete's resistance to chloride ingress and thus a key parameter for predicting the onset of corrosion-induced bond degradation. The random forest model achieved the highest prediction accuracy ( $R^2 = 0.91$ ), and the feature importance analysis revealed that the water-to-binder ratio and the binder type (particularly the use of fly ash or slag) were the dominant factors influencing chloride resistance.

A convolutional neural network (CNN)-based deep learning approach was proposed for predicting surface chloride concentration of concrete in marine tidal zones [88]. This study addressed the challenge that the chloride concentration at the concrete surface ( $C_s$ ) is not a constant but varies with exposure time and environmental conditions. The authors used a one-dimensional CNN to process time-series data of environmental parameters (temperature, humidity, wind speed, and tidal level) and predict the time-dependent surface chloride concentration for a given concrete mix. The CNN model successfully captured the seasonal variations in  $C_s$ , which is critical for accurate service life prediction, because overestimation of  $C_s$  leads to conservative but costly designs, while underestimation risks premature corrosion and bond loss.

A third study on chloride transport employed deep learning to predict time-dependent chloride penetration in concrete exposed to a coastal environment [89]. The authors developed a feedforward deep neural network that took as input the concrete mix proportions, the exposure

duration, and the depth from the exposed surface, and output the chloride concentration profile at any given time. The model was trained on a large dataset collected from field exposure sites over a 10-year period. The DNN accurately reproduced the nonlinear chloride concentration profiles predicted by Fick’s second law of diffusion, but it also captured deviations from ideal diffusion behavior that arise from concrete’s heterogeneity, such as the effect of the interfacial transition zone between aggregate and paste. This study is particularly relevant to bond strength prediction because the chloride concentration at the steel depth determines the time to corrosion initiation, after which bond degradation begins. Finally, a study on predicting carbonation depth in fiber-reinforced ultra-high performance concrete (FR-UHPC) using state-of-the-art machine learning techniques [90] addressed the other primary cause of reinforcement corrosion. The authors compiled a dataset of accelerated carbonation tests on UHPC specimens with various fiber types and dosages. They trained multiple ML algorithms, including ANN, random forest, and XGBoost, to predict the carbonation depth after a given exposure time. The XGBoost model achieved the highest accuracy, and the SHAP analysis revealed that the exposure time and the fiber volume fraction were the dominant predictors, with higher fiber contents reducing the carbonation rate by creating a more tortuous pathway for CO<sub>2</sub> diffusion. The accurate prediction of carbonation depth is essential for estimating the time at which the protective passive layer on the steel reinforcement is depassivated, after which active corrosion and bond degradation commence.

**H. Prediction of Failure Modes, Slip Behavior, and Structural Capacity**

Beyond the direct prediction of bond strength values, a growing body of research has expanded the scope of machine learning applications to encompass the prediction of associated failure mechanisms, the complete bond-slip constitutive relationship, and the structural-level capacities that depend on the integrity of the steel-concrete interface. This thematic cluster represents a significant maturation of the field, as researchers move from estimating a single scalar output (bond strength) toward modeling the full nonlinear mechanical response and the conditions under which different failure modes prevail. The ability to predict whether a bond connection will fail by bar pull-out, by concrete splitting, or by yield of the reinforcement has direct implications for design safety, while the accurate prediction of the load-slip curve is essential for nonlinear finite element analysis and performance-based design. Furthermore, models that predict structural capacities—such as the flexural strength of beams, the axial capacity of columns, or the shear strength of connections—serve as a critical bridge between laboratory-scale bond characterization and the real-world performance of complete structural systems. The studies within this cluster are systematically categorized in Table 8, which provides a two-level taxonomy based first on the type of predicted response and second on the specific application or focus of the model.

**Table 8. Taxonomy of machine learning studies on prediction of failure modes, slip behavior, and structural capacity.**

Predicted Response	Specific Application / Focus	Sources
<b>Bond Stress–Slip Behavior</b>	Bond stress-slip under static and dynamic loading	[28]
	Historical RC bond-slip model (few specimens)	[29]
	Mapping function for bond-slip and bond strength	[23]
	Load-slip curves of shear stud connectors	[91]
<b>Failure Mode Classification</b>	Bond-slip failure mode (pull-out vs. splitting)	[26], [20]
	Failure mode of PBL shear connectors	[83]
	Bond failure in beam-column joints	[92]

Predicted Response	Specific Application / Focus	Sources
<b>Structural Member Capacity</b>	Flexural capacity (beams)	[84], [93]
	Lateral load capacity of columns	[94]
	Axial compression capacity of columns	[95]
	Shear strength of SFRC deep beams	[96]
	Moment redistribution in statically indeterminate members	[97]
<b>Structural Response Prediction</b>	Backbone curve for corroded RC columns	[37]
	Crack propagation and crack mouth opening	[98], [99]
	Concrete breakout strength of anchors in SFRC	[100]
	Demane-to-capacity ratio for column jacketing	[101]
<b>Tensile Strength of Reinforcing Bars</b>	Tensile strength of spliced and non-spliced bars	[102]
<b>Structural Component Behavior</b>	Behavior of ECC-CES columns	[95]
	Behavior of elliptical double steel columns	[103]
<b>Deterioration &amp; Confinement Effects</b>	Bond strength deterioration under cyclic loads	[104]
	Bond-slip in cylindrical elements confined with stirrups	[105]
	Bond strength in beams with internal confinement	[106]
<b>Crack Detection &amp; Bond Diagnostics</b>	Crack detection in concrete surrounding reinforcement	[107]
<b>Validation of Existing Models</b>	Validation of RC bond stress-slip models	[108]

The prediction of the complete bond stress-slip curve represents a significant step beyond the estimation of peak bond strength alone. One study integrated finite element (FE) and deep learning methods to predict the bond stress-slip behavior of reinforcing bars in concrete under both static and dynamic loading conditions [28]. The authors generated a large synthetic dataset by varying the concrete compressive strength, bar diameter, embedment length, and loading rate in a validated FE model, and then trained a deep neural network to predict the entire stress-slip curve as a sequence of output values. The DL model successfully captured the nonlinear ascending branch, the peak stress, and the softening branch of the bond-slip curve, and it generalized well to loading rates that were not included in the training set. This approach demonstrates the feasibility of using ML to replace computationally expensive FE simulations for parametric studies of bond behavior under impact or seismic loading.

A different study tackled the challenge of data scarcity by developing an improved meta-learning neural network to predict the historical reinforced concrete bond-slip model using only a few test specimens [29]. Meta-learning, or “learning to learn,” enabled the model to be trained on a diverse set of bond test databases and then fine-tuned on a small number of new specimens from a specific structure of interest. The meta-learned model accurately captured the bond-slip characteristics of historical reinforced concrete elements, where detailed material testing is often not feasible, and it provided a practical tool for the assessment of heritage structures. Another investigation developed a mapping function using genetic programming to estimate the bond-slip behavior and bond strength of RC beams simultaneously [23]. The GP model produced an explicit mathematical expression that related the bond stress at any slip level to the concrete compressive strength, the bar diameter, and the cover depth, offering a design-oriented

equation that could be implemented in spreadsheet-based design software.

At the component level, the prediction of load-slip curves for shear stud connectors in solid concrete slabs was addressed using several machine learning models [91]. The study compiled a large database of push-out tests on headed stud connectors, and trained ANN, random forest, and gradient boosting models to predict the complete load-slip response as a function of the stud diameter, the stud height, the concrete compressive strength, and the degree of shear connection. The gradient boosting model provided the most accurate predictions, and the authors demonstrated that the ML-generated load-slip curves could be directly used in nonlinear finite element models of composite steel-concrete beams, replacing the need for empirical load-slip equations that are often inaccurate for non-standard geometries or material grades.

The classification and prediction of failure modes is another critical application within this cluster. The distinction between pull-out failure and splitting failure is fundamental for design, as each mode has different implications for structural ductility and collapse mechanism. One study developed a sparrow search algorithm-optimized extreme learning machine (SSA-ELM) model specifically for the classification and prediction of deformed steel and concrete bond-slip failure modes [26]. The SSA-ELM model was trained on a dataset of pull-out tests where the failure mode was visually identified, with input features including the concrete cover-to-bar diameter ratio, the stirrup confinement index, the concrete compressive strength, and the embedment length. The model achieved a classification accuracy of 97%, which was significantly higher than that of a standalone ELM or a support vector machine classifier. A separate investigation employed an intelligent algorithm-optimized support vector machine to predict both the bond strength and the failure mode of recycled aggregate concrete, achieving similarly high classification accuracy [20].

The failure mode of perfobond shear connectors (PBLs) in steel-concrete composite structures was

also studied using an interpretable ensemble learning framework [83]. The model distinguished between three failure modes: concrete crushing, shear connector yielding, and a combined mode. The SHAP analysis revealed that the concrete compressive strength and the hole diameter of the perfobond connector were the most influential parameters governing the failure mode. The bond failure in reinforced concrete beam-column interior joints, which can occur as either a splitting failure or a side-face blowout before the beam reinforcement reaches its yield strength, was extensively analyzed [92]. This study proposed an empirical formula for bond strength that considered the bond characteristics of beam flexural rebar in interior joints, specifically focusing on the concrete compressive strength as the primary variable; however, the authors noted that machine learning models could potentially capture the more complex interactions between joint geometry and confinement that their simplified equation could not.

Several studies have extended ML prediction to the capacity of complete structural members whose performance is governed by bond integrity. The flexural crack width of RC beams, which is directly influenced by the bond-slip relationship between steel and concrete (tension stiffening), was predicted using interpretable machine learning algorithms [84]. The study compared ANN, random forest, and XGBoost models, with XGBoost achieving the highest accuracy. The SHAP analysis identified that the tensile reinforcement ratio and the concrete cover were the most influential predictors, and the partial dependence plots confirmed the physically expected trends: increasing the reinforcement ratio reduced the crack width, while increasing the cover depth increased it. The prediction of long-term deflections in RC flexural structures was addressed using machine learning, where the model incorporated creep and shrinkage effects implicitly through the input of time-dependent parameters [93].

For columns, one study developed machine learning models to predict the maximum lateral load of reinforced concrete columns, comparing

traditional ML, deep learning, and structural analysis software [94]. The deep learning model outperformed both the traditional ML models and the structural analysis software in predicting the lateral load capacity, particularly for columns with high axial load levels where bond degradation and concrete spalling interact in a complex manner. Another investigation used adaptive sampling and machine learning techniques to predict the axial compression capacity of ECC-CES columns [95]. The engineered cementitious composite (ECC) layer provides increased confinement and ductility, and the ML model successfully captured the synergistic effect between the ECC jacket and the steel core, with the axial capacity being strongly influenced by the ECC thickness and the yield strength of the steel tube. The prediction of shear strength of steel fiber reinforced concrete deep beams was addressed using a hybrid neuro-swarm model that combined a neural network with particle swarm optimization [96]. The model accurately predicted the shear capacity, and the sensitivity analysis showed that the shear span-to-depth ratio and the fiber volume fraction were the dominant parameters. An XGBoost-based model was developed to predict the moment redistribution in statically indeterminate reinforced concrete flexural members, which is a structural-level response that depends on the ductility of the plastic hinge region, which in turn is influenced by the bond-slip behavior of the reinforcement [97].

The prediction of complete structural response curves, rather than just peak capacities, has also been investigated. An ensemble learning-based approach was used to predict the backbone curve for corroded reinforced concrete columns [37]. The backbone curve, which defines the envelope of the cyclic response, was parameterized by the yield displacement, the yield force, the peak force, and the post-peak softening slope. The ensemble model predicted these parameters with high accuracy, and the authors demonstrated that the predicted backbone curves could be used to construct simplified nonlinear models for seismic assessment of existing RC structures with corroded reinforcement.

The estimation of crack propagation and crack mouth opening displacement in concrete using machine learning algorithms represents a related application [98], [99]. One study used the voronoi diagram algorithm to examine the crack pattern and propagation on a random concrete surface [98], providing a novel approach to visualize and predict crack networks that can be used to infer bond quality, as bond failure is often accompanied by the formation of longitudinal splitting cracks along the reinforcement. Another study specifically focused on the machine learning-based prediction of crack mouth opening displacement in ultra-high-performance concrete [99], which is directly related to the pull-out capacity of reinforcing or prestressing strands embedded in the UHPC.

The concrete breakout strength of anchors in steel fiber reinforced concrete was predicted based on material test datasets using machine learning [100]. While anchors are not reinforcing bars, the breakout failure of an anchor under tension is analogous to the splitting failure of a deformed bar with a short embedment length, and the ML model revealed that the fiber factor and the embedment depth were the most critical parameters. A machine learning approach was also developed to predict the demand-to-capacity ratio for reinforced concrete jacketing of columns in seismic-deficient buildings [101]. The model used the geometry and material properties of the existing column and the jacket as inputs, and it predicted the capacity enhancement factor that should be applied to the original column's strength. The study confirmed that ML models could replace time-consuming nonlinear pushover analyses for preliminary screening of large building stocks.

The tensile strength of spliced and non-spliced steel bars was predicted using machine learning- and regression-based methods [102]. The model focused on the axial load capacity of lapped splices, which is directly governed by the bond strength of the lapped bars, and demonstrated that ML models could provide more accurate predictions of splice strength than the current design code provisions. The behavior of elliptical double steel columns under compression loading

was predicted using machine learning [103], where the model accounted for the effect of partial bond between the outer steel tube and the concrete infill.

The deterioration of bond strength under reversed cyclic loads, which is critical for seismic design, was investigated for reinforced and prestressed concrete members [104]. The study developed an ML model that could capture the progressive loss of bond capacity as a function of the cyclic displacement amplitude and the number of cycles, revealing that bond deterioration was more severe in prestressed members due to the higher initial bond stresses. The bond slip model in cylindrical reinforced concrete elements confined with stirrups was validated through an analytical strain distribution comparison [105]. The study proposed new design equations for the maximum bond stress and the residual bond stress in confined concrete, and the analytical model was shown to be accurate for both pull-out and splitting failure modes when validated against a comprehensive database of experimental tests. A Bayesian probabilistic model was introduced for the steel-concrete bond strength in beams with internal confinement, addressing the inherent limitations of conventional deterministic design models by providing a probabilistic distribution of the bond capacity [106]. The Bayesian model naturally quantified the uncertainty in bond strength predictions, which is essential for reliability-based design.

Finally, two studies focused on diagnostic and validation applications. One used artificial neural networks and non-destructive testing to detect cracks in the concrete surrounding embedded steel reinforcement [107], establishing a direct link between surface crack patterns and the internal bond condition. The other provided a validation framework for existing RC bond stress-slip models through an analytical strain distribution comparison [108], demonstrating that while many empirical models in the literature can predict the peak bond stress, they often fail to accurately reproduce the strain distribution along the bar, which is critical for serviceability limit state calculations.

#### IV. DISCUSSION

The synthesis of the 101 studies included in this systematic review reveals a field that has undergone a profound transformation over the past five years. Taken together, the findings consistently indicate that machine learning models offer a substantial improvement in predictive accuracy over traditional empirical formulas for bond strength, particularly when applied to complex scenarios involving material degradation, specialized concretes, or alternative reinforcement types. What emerges across the literature is a clear pattern: ensemble methods and hybrid models that combine a base learner with an optimization algorithm or a metaheuristic search strategy consistently achieve the highest coefficients of determination and the lowest prediction errors across diverse datasets. This is not merely a reflection of increased model complexity but rather an indication that the bond strength problem—with its inherently nonlinear, multivariate interactions—requires the flexibility that ensemble averaging and hyperparameter tuning provide. For example, the stacking ensemble for fire resistance prediction [70] and the sparrow search algorithm-optimized extreme learning machine for failure mode classification [26] both demonstrated that the combination of multiple weak learners or the intelligent optimization of a single learner can extract more information from the available data than any standalone algorithm can achieve alone. A critical finding that permeates multiple thematic clusters is the superior performance of machine learning models for bond strength prediction in the presence of reinforcement corrosion. Corrosion introduces a complex, time-dependent degradation of the steel-concrete interface that traditional empirical formulas treat with a simple multiplicative reduction factor, if they consider it at all. The machine learning studies in this review, however, show that models incorporating explicit corrosion parameters—such as mass loss, corrosion current density, or crack width—can capture the nuanced progression from initial confinement enhancement to subsequent bond degradation [30], [38]. This is a significant theoretical implication: it suggests that data-

driven models are not merely curve-fitters but can actually learn the underlying physical mechanisms of the corrosion process, provided that sufficiently detailed experimental inputs are available. The practical implication for infrastructure assessment is clear: a properly trained machine learning model, deployed within a graphical user interface or a software tool, could allow field engineers to input measurable corrosion indicators from a visual inspection or a half-cell potential survey and obtain a reliable estimate of the residual bond capacity of an existing structure.

The integration of explainable artificial intelligence techniques, particularly SHAP analysis, represents another cross-cutting theme that has reshaped the field. Consistently found across the reviewed studies, SHAP values have been used to identify the most influential features governing bond strength predictions, and these insights have nearly always aligned with established mechanical intuition. For example, the dominance of the concrete cover-to-bar diameter ratio and the corrosion level in models for corroded reinforcement [30], or the importance of the recycled aggregate replacement ratio in models for sustainable concretes [109], strongly corroborates the findings of decades of experimental research. This convergence between data-driven feature importance and domain knowledge is not accidental; it suggests that machine learning models are learning physically meaningful relationships rather than spurious correlations. The theoretical implication is that explainable AI can serve as a powerful tool for hypothesis generation in structural engineering, potentially revealing subtle interactions between parameters that have been overlooked in past experimental programs. The practical implication is that engineers can trust and adopt these models with greater confidence, as they can verify that the model's decision-making logic is consistent with their own understanding of the mechanics of the bond problem.

Nevertheless, the thematic cluster on environmental effects, particularly fire exposure, reveals a significant gap in the literature. While the studies on fire resistance of FRP-strengthened

concrete members are methodologically rigorous and demonstrate the clear advantage of ensemble learning [70], [71], there is a conspicuous absence of studies that apply machine learning to predict the bond strength of ordinary steel reinforcement in concrete exposed to fire without the presence of FRP. The bond degradation mechanism under fire is fundamentally different from corrosion-induced degradation; it involves thermal expansion mismatch, dehydration of the cement paste, and potential spalling, none of which are easily represented by simple empirical parameters. The studies on alkali-activated slag concrete at elevated temperatures [62] provide a promising starting point, but they are limited to a single binder type. This gap is particularly concerning given that fire is one of the most extreme design loads for reinforced concrete structures, and the current design codes rely on simplified temperature-dependent reduction factors that are known to be inaccurate for high-strength concretes and lightweight aggregates.

Another notable limitation that pervades the literature is the issue of dataset quality and availability. While many studies compile extensive databases from published experimental results, there is no standardized benchmark dataset for bond strength prediction. The datasets differ in their feature sets, their measurement protocols (pull-out tests vs. beam-end tests vs. splice tests), and their sample sizes, making direct comparison of model performance across studies difficult. Furthermore, the vast majority of the studies reviewed here rely on datasets that are heavily skewed toward conventional concrete with normal-strength steel and moderate cover depths. Models trained on such datasets may not generalize to the edge cases that are most critical for design: high-strength concrete with large-diameter bars, lightweight aggregate concrete with low cover, or concrete with high levels of corrosion damage. The potential for publication bias is also relevant here; studies that report high coefficients of determination are more likely to be published, while studies that achieve modest accuracy or expose model limitations may remain unpublished. This bias could create an overly optimistic impression of the current state of the

art in machine learning for bond strength prediction.

The modeling of slip behavior and failure modes, while growing rapidly, remains a methodological challenge. The studies on bond stress-slip curve prediction [28], [29] are impressive in their ambition, but they face the fundamental problem that the bond-slip curve is not a single scalar value but a vector of length variable depending on the slip level. The deep learning approaches that treat the curve as a sequence prediction problem show promise, but they require careful alignment of the slip axis across different specimens, which is not straightforward when the peak bond stress occurs at different slip values. More critically, the prediction of failure modes is often treated as a static classification problem, yet the actual failure mode of a bond connection can change depending on the loading rate, the state of corrosion, or the presence of transverse pressure. The reviewed studies that incorporate these dynamic effects are rare, and the models that do not may be providing misleadingly high classification accuracy on datasets where the failure mode is determined primarily by geometric parameters.

The theoretical implications of this review extend beyond the narrow domain of bond strength prediction. The successful application of machine learning to this problem suggests that many other empirical relationships in structural engineering—such as shear strength of beams, punching shear of slabs, or confinement models for columns—could benefit from a similar data-driven re-examination. The findings of this review indicate that the key to successful application lies not in choosing the most complex algorithm but in the careful construction of the input feature space, the use of robust cross-validation strategies, and the integration of physically-informed constraints. The studies that employed physics-guided loss functions or monotonic network architectures [80], [110] are particularly instructive in this regard: they demonstrate that embedding domain knowledge into the learning process does not sacrifice accuracy but instead enhances both predictive reliability and trustworthiness. This finding challenges the common belief that

machine learning is purely a “black box” and suggests that the future of structural engineering modeling lies in hybrid approaches that combine the inductive power of data-driven learning with the deductive rigor of mechanics.

From a practical standpoint, the most actionable insight from this review is the availability of open-source or GUI-based software tools that allow practitioners to use pre-trained machine learning models without needing to understand the underlying algorithm. The development of such tools for bond strength prediction [30], while currently isolated, points toward a future where engineers can input readily available parameters (concrete strength, bar diameter, cover depth, corrosion level) and obtain not only a point estimate of bond strength but also a measure of prediction uncertainty and an explanation of the key contributing factors. This would represent a significant advancement over current design codes, which provide a single deterministic value for development length that is often overly conservative for well-confined, high-strength concrete, and unconservative for lightweight or corroded concrete.

However, adopting these models in practice will require a cultural shift within the structural engineering community. The current design paradigm, enshrined in codes such as ACI 318 and Eurocode 2, is based on prescriptive empirical formulas that are trusted precisely because they are simple, transparent, and have been validated over decades of successful use in practice. Machine learning models, no matter how accurate, will face resistance if they are not accompanied by a clear mechanism for validation against new experimental data, a protocol for updating as more data become available, and a transparent audit trail that allows engineers to understand why a particular prediction was made for their specific case. The work on explainability and physics-guided modeling reviewed here represents a crucial step in this direction, but it remains insufficient to fully address the trust deficit. Future efforts should focus on developing model cards—standardized documentation that describes the intended use, the training data composition, the performance across different

subgroups, and the known limitations—for every machine learning model proposed for engineering design.

In terms of methodological limitations of this review itself, several points warrant acknowledgment. The restriction to English-language publications likely excluded relevant work published in Chinese, Japanese, Spanish, or other languages, particularly given that much of the experimental research on bond behavior originates from non-English-speaking countries. The exclusion of grey literature, while necessary to maintain a quality baseline, may have omitted important datasets or negative results that could temper the optimistic conclusions drawn from peer-reviewed studies. The search strategy, despite careful construction, may have missed studies that use domain-specific terminology not captured by the keywords, such as “pull-out test data” without the phrase “machine learning.” Furthermore, the assessment of study quality was performed qualitatively and subjectively; while we focused on the reporting of performance metrics and the rigor of validation, we did not apply a formal quality scoring system. This limits the ability to draw meta-analytic conclusions about the comparative performance of different algorithms across studies.

Looking forward, the research gaps identified in this review suggest several compelling directions for future work. There is a pressing need for a community-wide effort to establish a standardized, publicly accessible benchmark database for bond strength prediction that includes diversified experimental setups (pull-out, beam-end, splice), a wide range of concrete compressive strengths (from 15 MPa to 150 MPa), various bar diameters and rib geometries, multiple levels of corrosion damage, and controlled environmental exposure conditions. Such a database would enable fair comparison of different machine learning algorithms and would accelerate the process of model refinement and validation. Future research should also explore the application of meta-learning or transfer learning to address the challenge of data scarcity in specific domains, such as bond strength in fiber-reinforced polymer bars embedded in

geopolymer concrete, where experimental data are limited. The studies on meta-learning for historical structures [29] provide a template for how this could be achieved.

The understudied area of bond behavior under simultaneous environmental and mechanical stressors—such as combined corrosion and cyclic loading, or combined fire exposure and impact—represents a crucial frontier. Most experimental tests and most machine learning models consider these stressors in isolation, yet real structures are exposed to multiple aggressive agents simultaneously. Future research should focus on generating experimental data under coupled conditions and then developing models that can disentangle the interacting effects. Generative adversarial networks or variational autoencoders could be employed to augment limited experimental data with synthetic samples that are physically plausible, as demonstrated in the prediction of split tensile strength of fiber-reinforced recycled aggregate concrete [57].

Finally, the development of probabilistic machine learning models that provide not only a point estimate of bond strength but also a full uncertainty quantification—aleatoric uncertainty from data noise and epistemic uncertainty from model limitations—should be prioritized. The Bayesian model for bond strength in beams with internal confinement [106] offers a valuable starting point. Such probabilistic models are essential for transitioning from deterministic design rules to reliability-based design frameworks, where the probability of bond failure is quantified and used to calibrate partial safety factors. This would align machine learning-based bond strength prediction with the fundamental philosophy of modern structural design codes and facilitate its acceptance by the engineering community.

## V. CONCLUSION

This systematic literature review synthesized 101 studies to map the landscape of machine learning applications for predicting the bond strength between steel reinforcement and concrete. Our analysis confirms that ensemble and hybrid models consistently outperform both traditional

empirical formulas and standalone algorithms across diverse application domains, particularly for datasets involving corrosion degradation or specialized concrete mixes. The integration of explainable AI techniques, most notably SHAP analysis, has emerged as a critical development that bridges the gap between predictive accuracy and engineering trustworthiness by revealing that models learn physically meaningful feature relationships. Furthermore, physics-guided modeling approaches that embed monotonic constraints or domain-specific loss functions demonstrate that accuracy and mechanical consistency are complementary rather than competing objectives.

The theoretical contribution of this review lies in its demonstration that machine learning can systematically capture the complex, nonlinear interactions governing bond behavior—interactions that traditional regression models cannot adequately represent. Practically, the findings underscore the potential for deploying interpretable, validated ML models as decision-support tools for condition assessment of corroded infrastructure and for designing with novel materials like recycled aggregate or geopolymers. Our analysis also identifies critical gaps that constrain the field's progress: the lack of standardized benchmark datasets, the underrepresentation of fire exposure effects, and the scarcity of models providing full uncertainty quantification alongside point predictions. Future research must prioritize the development of open-access, diversified experimental databases and the creation of probabilistic frameworks that align with reliability-based design philosophy. Addressing these gaps will be essential for transitioning machine learning-based bond strength prediction from a promising research tool into a widely adopted engineering practice.

## VI. REFERENCES

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