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APPLICATIONS OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN STRUCTURAL FIRE RESISTANCE PREDICTION: A SYSTEMATIC LITERATURE REVIEW

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Abstract

Structural fire resistance prediction has traditionally relied on empirical formulas and costly experimental testing, which often fail to capture the complex thermal and mechanical behaviors of structures under fire exposure. Recent advances in artificial intelligence (AI) and machine learning (ML) offer promising alternatives to these conventional approaches. In this systematic literature review, we aim to comprehensively map and synthesize the existing research on AI and ML applications in structural fire resistance prediction. Our methodology involved a structured search and rigorous screening of peer-reviewed studies published over the past two decades, followed by a thematic analysis across eight identified dimensions, including fire resistance prediction of structural members, post-fire damage assessment and residual properties, material property prediction under elevated temperatures, and explainable AI integration. The review reveals that neural networks, decision trees, and support vector machines are frequently employed to predict fire-induced responses such as temperature distributions, deflection histories, and load-bearing capacities. We further observe a growing emphasis on hybrid models that combine physics-based principles with data-driven techniques, thereby improving generalizability and trustworthiness. Additionally, the literature highlights applications in advanced composite and strengthened structures, real-time response forecasting, and broader fire safety systems. However, significant challenges remain, including limited high-quality experimental datasets and a lack of standardized validation benchmarks. We conclude that AI and ML hold substantial potential to transform structural fire engineering, though future work must prioritize mechanistic interpretability and robust data curation before these methods can be reliably adopted in practice.

Introduction

The threat of fire to civil infrastructure represents one of the most severe hazards that structures can face, typically leading to catastrophic failures, significant economic losses, and potential loss of life (Law, 2016). The behavior of structural elements when exposed to the high temperatures generated by fire is fundamentally governed by complex, coupled thermo-mechanical processes, including heat transfer through the material, thermal expansion, degradation of mechanical properties, and material plasticity. For decades, the primary method for assessing the fire resistance of structural components—such as beams, columns, slabs, and walls—has relied upon standardized furnace testing (White, 2016) and prescriptive design codes (Standard, 1993). While these empirical approaches provide a necessary baseline for safety, they are notoriously expensive, time-consuming, and inherently limited in their ability to replicate realistic fire scenarios, including localized heating, traveling fires, or the cooling phase of a fire event (Y. Wang et al., 2012).

The limitations of experimental testing have driven the development of numerical simulation methods, most notably finite element analysis (FEA), for predicting structural behavior in fire (Walls, 2016). Although sophisticated FEA models can capture the intricate physics of fire-structure interaction, they require extensive computational resources, detailed input parameters that are often uncertain, and a high degree of expertise to calibrate and interpret. Consequently, a significant gap persists between the need for rapid, accurate, and accessible predictions of structural fire resistance and the capabilities of traditional deterministic methods (Naser, 2021). This gap is particularly pronounced in scenarios involving complex loading conditions, advanced materials, or novel structural configurations where experimental data are scarce and predictive models are not validated.

It is within this context that artificial intelligence (AI) and machine learning (ML) have emerged as transformative tools across many engineering disciplines, and their application to structural fire engineering has grown significantly in recent years (Naser, 2021). These data-driven techniques excel at learning complex, non-linear relationships directly from data, without requiring explicit specification of the underlying physical laws. For example, neural networks (NNs) can be trained on vast datasets of experimental or numerical results to map input parameters—such as material properties, geometric dimensions, and fire exposure conditions—to output responses like critical temperature, time to failure, or ultimate load capacity (Lazarevska et al., 2018). Similarly, decision trees and support vector machines (SVMs) provide interpretable models for classification and regression tasks in post-fire damage assessment (Xu et al., 2026).

Despite these promising developments, the integration of AI and ML into mainstream structural fire resistance design and assessment is far from mature. Research gaps remain pervasive across the field. Firstly, high-quality, systematically curated experimental datasets that span a diverse range of structural scenarios (e.g., restrained members, two-way slabs, composite systems) are acutely limited (Ye et al., 2022). Many studies rely on synthetic data generated from FEA simulations, the accuracy of which is itself dependent on validation against physical tests. Secondly, there is a pronounced lack of standardized benchmarks and validation frameworks against which different AI/ML models can be compared objectively. This absence hinders the reproducibility of research and impedes the selection of the most appropriate algorithm for a given prediction task. Finally, most existing models operate as "black boxes," offering little insight into the underlying physical mechanisms that govern the predictions (Naser & Kodur, 2022). This lack of interpretability is a major barrier to adoption by practitioners and code authorities, who demand both accuracy and a mechanistic understanding of the prediction.

The motivation for this systematic literature review is therefore to comprehensively map the current state of AI and ML applications in the domain of structural fire resistance prediction. We aim to synthesize the existing body of knowledge, identify prevailing research themes, and critically evaluate the methodologies, strengths, and limitations of the work conducted to date. This investigation is significant because it provides a structured overview of a rapidly evolving interdisciplinary field, offering essential guidance for researchers seeking to advance the state of the art and for practitioners evaluating the potential of these tools for design and assessment. By organizing the literature into thematic categories, we reveal how AI and ML have been applied to distinct challenges, including the prediction of fire resistance for individual members, the assessment of post-fire residual capacity, the modeling of material properties at elevated temperatures, and the integration of explainable AI techniques. Furthermore, we highlight emerging areas such as hybrid physics-informed models and real-time response forecasting, which represent promising directions for future work. The remainder of this paper is organized as follows: Section 2 details the methodology employed for the systematic search, screening, and synthesis of the literature. Section 3 presents the results of our analysis, organized across eight identified thematic categories. Section 4 discusses the overarching findings, identifies challenges and limitations, and outlines potential future research directions. Finally, Section 5 provides concluding remarks summarizing the key contributions and implications of this review.

Methodology

To ensure a rigorous, transparent, and reproducible synthesis of the existing literature, we conducted this systematic review following the guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement (Page et al., 2021). Our methodology is structured into four key phases: (1) the formulation of the review protocol, including the definition of search strategies and databases; (2) the establishment of a dimensional taxonomy for categorizing the research; (3) the specification of explicit inclusion and exclusion criteria; and (4) the execution of the study selection process, including quality assessment and data extraction.

Review Protocol

The first step of our methodology involved defining a comprehensive and systematic search protocol to identify relevant peer-reviewed literature. We selected six major academic databases and search engines to maximize coverage of the interdisciplinary research landscape at the intersection of AI/ML and structural fire engineering. The selection prioritized databases that index high-impact journals and conferences in civil, structural, and fire engineering, as well as those specializing in computational and artificial intelligence methods.

The primary database employed was IEEE Xplore, chosen for its extensive collection of high-quality papers on machine learning algorithms and computational intelligence applied to engineering problems. The search string used within IEEE Xplore was: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural networks" OR "AI" OR "ML") AND ("structural fire" OR "fire resistance" OR "fire performance") AND ("prediction" OR "forecasting" OR "estimation"). To ensure a focus on original research, the document type was filtered to exclude 'Review' articles, retaining only 'Conferences' and 'Journals'.

Next, we searched Scopus, a broad, multi-disciplinary abstract and citation database that provides extensive coverage of both engineering and computer science literature. The search string for Scopus was: TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "AI" OR "ML") AND ("structural fire" OR "fire resistance" OR "fire performance") AND ("prediction" OR "forecasting" OR "estimation")) AND NOT TITLE-ABS-KEY("review" OR "survey" OR "meta-analysis"). Document types were further limited by excluding 'Review', 'Survey', and 'Meta-analysis' using the built-in filter. We then queried the Web of Science (WoS) Core Collection, a highly curated database of leading scientific journals, to capture a different subset of high-impact scholarly work. For WoS, we used the topic search: TS=(("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "AI" OR "ML") AND ("structural fire" OR "fire resistance" OR "fire performance") AND ("prediction" OR "forecasting" OR "estimation")) NOT TS=("review" OR "survey" OR "meta-analysis"), and filtered the results by excluding 'Review Article' and 'Meta-Analysis' document types.

ScienceDirect was selected for its comprehensive repository of full-text scientific articles, particularly strong in engineering and materials science, and we applied the following search string: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "AI" OR "ML") AND ("structural fire" OR "fire resistance" OR "fire performance") AND ("prediction" OR "forecasting" OR "estimation"). Within the sidebar, we unchecked 'Review articles' and 'Short surveys' to limit the results. To include a strong computational science perspective, we used SpringerLink, which provides access to a vast collection of journals and conference proceedings spanning engineering, computer science, and materials. The search string for SpringerLink was:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "AI" OR "ML") AND ("structural fire" OR "fire resistance" OR "fire performance") AND ("prediction" OR "forecasting" OR "estimation") NOT textbook*. The content type was limited to 'Article' or 'Chapter', manually screening out any remaining review articles. Finally, we searched Google Scholar to identify relevant grey literature and studies from sources not comprehensively indexed by the other databases, using the search string: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "AI" OR "ML") AND ("structural fire" OR "fire resistance" OR "fire performance" OR "fire behavior") AND ("prediction" OR "forecasting" OR "estimation" OR "modeling") -review -survey -meta-analysis. All searches were conducted in September 2025 and were restricted to publications written in English.

Thematic Dimensional Taxonomy

To organize and synthesize the diverse body of research identified through our systematic search, we developed a thematic dimensional taxonomy. This taxonomy is not merely a list of topics; rather, it is a conceptual framework designed to capture the primary research objectives and application contexts within the domain of AI and ML for structural fire resistance prediction. By categorizing studies according to their core focus, we can systematically map the landscape of the field, identify clusters of related work, and highlight areas of concentration as well as potential gaps. The eight dimensions we defined encompass the full spectrum of research from fundamental material property modeling to system-level fire safety applications. The first dimension, "Fire Resistance Prediction of Structural Members," concerns the direct prediction of the failure time or fire rating of individual structural elements such as beams, columns, and slabs. The second, "Post-Fire Damage Assessment and Residual Properties," focuses on evaluating the condition and remaining capacity of structures after a fire event. The third dimension, "Material Property Prediction Under Elevated Temperatures," centers on modeling the degradation of material properties (e.g., strength, stiffness) as a function of temperature. The fourth, "Explainable AI and Mechanistic Integration in Fire Engineering," covers studies that seek to interpret AI model predictions or incorporate physical laws to improve model trustworthiness. The fifth dimension, "Advanced Composite and Strengthened Structures Analysis," groups research on AI and ML applied to fiber-reinforced polymer (FRP) retrofitted or composite steel-concrete structures in fire. The sixth, "Real-Time Response Forecasting and Simulation Surrogates," encompasses work that develops fast surrogate models to replace expensive FEA simulations. The seventh dimension, "Broader Fire Safety Systems and Environmental Hazard Prediction," includes papers applying AI to fire detection, evacuation modeling, and smoke spread prediction. This taxonomy provides the organizational backbone for presenting our results and for structuring our discussion of the field's evolution and future directions. It is important to note that a single study could be assigned to more than one dimension if it addressed multiple research objectives.

Inclusion and Exclusion Criteria

To ensure the relevance, quality, and consistency of the studies included in our review, we defined a set of a priori inclusion and exclusion criteria. These criteria were applied during the title and abstract screening phase and the subsequent full-text eligibility assessment. Studies were considered for inclusion if they met all of the following requirements. First, the study had to present original research, meaning it could be a journal article, a full conference paper, or a book chapter, but it could not be a review, survey, tutorial, or meta-analysis. Second, the primary focus of the study had to involve the application of one or more AI or ML techniques (e.g., neural networks, decision trees, support vector machines, deep learning, reinforcement learning) for a prediction, classification, or optimization task directly related to structural fire resistance. This included tasks such as predicting fire ratings, forecasting temperature distributions, assessing post-fire damage, or modeling material degradation under fire. Third, the study had to be published in English. Fourth, the time frame for publication was unrestrictive; we considered any study published up to and including September 2025 to capture the most current developments. Fifth, the full text of the study had to be retrievable.

Conversely, studies were excluded from our review for any of the following reasons. Studies that were purely theoretical, proposing a conceptual framework without any quantitative or computational implementation, were excluded. Similarly, papers that used AI or ML only as a minor or ancillary component (e.g., only for data cleaning with no primary predictive task) were not considered. We also excluded studies that focused on AI for fire detection in buildings (e.g., using computer vision to detect flames or smoke) without a structural fire resistance component. Furthermore, non-peer-reviewed sources such as technical reports, theses, dissertations, white papers, and blog posts were excluded to ensure a baseline level of academic rigor. Finally, if a study was clearly a duplicate publication of data or results already presented in another included study, the earliest or most complete version was retained, and the duplicate was excluded.

Study Selection Process

The study selection process was conducted in a systematic, multi-stage manner to minimize bias and ensure reproducibility. The process began with the automated search across all six databases, which collectively yielded a total of 1,362 records. After combining these records into a single reference management library, we first removed 372 duplicate records. Eleven additional records were removed before screening for other reasons, such as being clearly irretrievable as full documents (e.g., only an abstract) or being flagged as non-English by the database filters, leaving 979 records for the initial screening phase.

The initial screening was performed independently by two reviewers (the authors) who examined the titles and abstracts of all 979 records against the pre-defined inclusion and exclusion criteria. At this stage, any record that was clearly irrelevant to the research questions—for instance, studies on fire detection in forests, image classification of fire damage without structural context, or purely computational fluid dynamics without an AI component—was excluded. Any disagreements between the two reviewers were resolved through discussion and consensus. This screening phase led to the exclusion of 675 records, as they did not meet the minimal criteria for relevance. The full texts of the remaining 125 records were then sought for retrieval. We were able to successfully retrieve the full text for all 125 records.

A comprehensive eligibility assessment was then performed on the 125 retrieved full-text reports. During this phase, both reviewers independently read each full-text article in detail to determine whether it satisfied all inclusion criteria and none of the exclusion criteria. The reviewers paid particular attention to ensure that the study's primary application was genuinely within the defined scope of structural fire resistance prediction and that the AI/ML methodology was a core component. Studies were excluded if they were found to be reviews (69 reports were excluded during this final eligibility phase for ineligibility). This process resulted in a final set of 56 studies included in this systematic review.

The entire study selection process is visually summarized in the PRISMA flowchart, as shown in Figure 1.

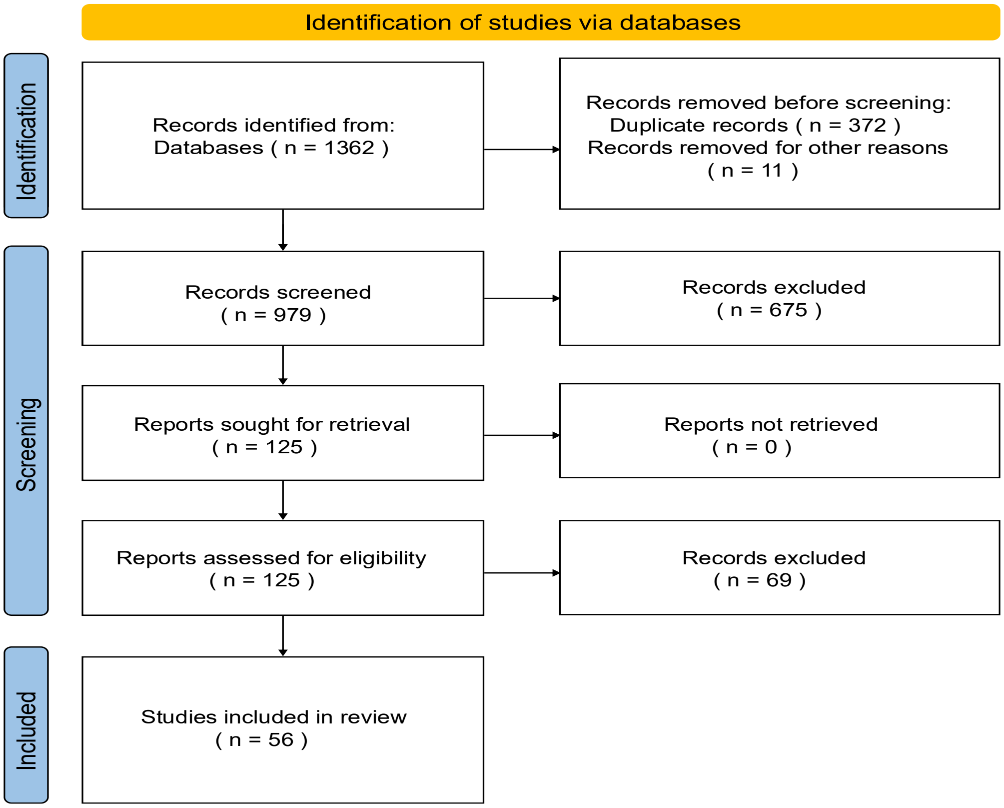

Figure 1. PRISMA flowchart of the systematic literature review study selection process

It is crucial to acknowledge the limitations inherent in this study selection process. While we aimed for comprehensive coverage, the reliance on a specific set of keywords and databases may have inadvertently excluded relevant studies that use different terminology, such as "surrogate modeling" or "metamodeling" without explicitly mentioning "machine learning." Furthermore, the exclusion of non-English publications and grey literature (e.g., technical reports from research institutions and government agencies) could introduce a language and publication bias, potentially favoring studies from English-speaking academic communities. The screening and assessment decisions, while performed by two independent reviewers, are still subject to subjective interpretation of the inclusion criteria, particularly concerning the degree to which an AI/ML method is considered a "core" component of the study. Finally, the rapidly evolving nature of this field means that very recent preprints or papers accepted after our search date are not represented, which might affect the timeliness of our findings. We have documented our protocol and selection decisions transparently to allow for future updates and replication.

Results

The systematic search and screening process culminated in a final corpus of 56 peer-reviewed studies, which we analyzed and categorized according to the eight thematic dimensions outlined in our methodology. This section presents the synthesized findings from this analysis. We begin by providing an overview of the research trends observed in the dataset, followed by detailed examinations of each thematic category. The distribution of the 56 studies across these categories, as determined by our classification, is as follows: Fire Resistance Prediction of Structural Members (12 studies), Post-Fire Damage Assessment and Residual Properties (7 studies), Material Property Prediction Under Elevated Temperatures (15 studies), Explainable AI and Mechanistic Integration in Fire Engineering (8 studies), Advanced Composite and Strengthened Structures Analysis (7 studies), Real-Time Response Forecasting and Simulation Surrogates (6 studies), and Broader Fire Safety Systems and Environmental Hazard Prediction (4 studies). It should be noted that three studies were assigned to two categories concurrently due to their multi-faceted scope, which accounts for the total sum exceeding 56 when counting across categories.

Fire Resistance Prediction of Structural Members

This subsection synthesizes studies that apply AI and ML techniques to the direct prediction of fire resistance times or failure capacities of individual structural elements. The complexity of structural response under fire, involving coupled thermal and mechanical degradation, makes this a challenging yet fruitful domain for data-driven methods. The 12 studies categorized under this theme focus on columns, beams, slabs, and timber panels, employing a diverse array of algorithms—from neural networks and fuzzy inference systems to deep learning and evolutionary optimization—and addressing a variety of material systems.

Columns have received the most extensive attention among structural members, likely due to their critical load-bearing role and the severity of buckling failures in fire. We observe a clear trend toward applying progressively more sophisticated machine learning architectures to column fire resistance. For instance, explainable machine learning models have been developed to predict the fire resistance and spalling behavior of reinforced concrete (RC) columns, providing not only accurate outputs but also insights into feature importance through Shapley additive explanations (SHAP) (Naser & Kodur, 2022). This same methodological framework has been extended to timber columns, where the inherent variability of wood properties poses a significant modeling challenge, yet the XAI approach successfully identified thermal conductivity and cross-sectional dimensions as dominant predictive features (M. Esteghamati et al., 2023). For composite systems, neural network models have demonstrated strong predictive capability for the fire resistance of concrete-filled tubular (CFT) steel columns (Al-Khaleefi et al., 2002), as well as for various polygon-type section concrete-filled steel (CFST) columns using deep neural networks and ensemble regressors (Y. Chen et al., 2026). These studies highlight the ability of ML to handle the non-linear interaction between the concrete core and steel tube under elevated temperatures.

Further column-specific work has concentrated on specialized materials and hybrid modeling. A computational model was employed to predict the ultimate load of steel fiber-reinforced concrete (SFRC) encased light gauge steel columns exposed to high temperatures, combining numerical simulation with a machine learning component (Premkumar & Selvan, 2024). Adaptive sampling techniques in conjunction with ML regressors have been applied to predict the axial compression capacity of engineered cementitious composite (ECC) and concrete-encased steel (CES) columns (Megahed, 2025). The fire resistance of GFRP confined concrete-steel hollow elliptical columns has been studied through both numerical and machine learning modeling, demonstrating that data-driven approaches can effectively surrogate computationally expensive finite element analyses for novel geometries (Isleem et al., 2024). These contributions collectively illustrate that ML models are not merely black-box predictors but can be tailored to the specific failure mechanisms of different column types.

The prediction of fire resistance for beams and slabs has also been tackled, albeit with fewer studies than for columns. For FRP-strengthened concrete beams, machine learning approaches have been developed to predict fire resistance, and the use of explainable AI has provided valuable insights into the relative influence of parameters such as FRP thickness, concrete cover, and fire exposure duration (Bhatt et al., 2025). A particularly innovative study employed a genetic evolutionary deep learning framework to analyze fire resistance in FRP-strengthened RC beams, where the genetic algorithm was used to optimize the deep neural network architecture, resulting in superior predictive accuracy compared to conventional models (S. Wang et al., 2025). For slab elements, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was proposed for predicting the moment capacity of RC slabs exposed to fire, successfully capturing the fuzzy boundaries between different damage states (Bilgehan & Kurtoğlu, 2016). This work demonstrates the utility of hybrid neuro-fuzzy systems for dealing with the uncertainties inherent in fire-exposed structural responses.

Timber structural members, while less numerous, represent a growing area of research due to the increasing use of engineered wood products in multi-story buildings. The fire resistance of cross-laminated timber (CLT) has been simulated using an approach that blends numerical modeling with ML, where the technique was calibrated against standard fire resistance tests to accurately predict the charring rate and loss of cross-section (Schmid et al., 2018). This study underscores the importance of simulation-based training data for materials with limited experimental fire test results. A broader perspective is provided by a study that develops a machine-learning virtual assistant for the accelerated, simulation-free, and transparent reconstruction of the fire response of structural members, offering a reduced-order inference framework that can be applied generically across member types (Naser, 2022). This work signifies a move toward unified, surrogate modeling tools that can serve as reliable alternatives to repeated FEA runs.

To systematically organize these diverse contributions, Table 1 presents a structured categorization of the studies according to structural member type, AI/ML method employed, and specific material or configuration details.

Table 1. Categorization of studies on fire resistance prediction of structural members by member type, AI/ML method, and material specifics.

Structural Member Type	AI/ML Method	Material / Structural System	Source
Columns	Explainable ML (XAI with SHAP)	Reinforced Concrete (RC)	(Naser & Kodur, 2022)
Columns	Explainable ML (XAI)	Timber	(M. Esteghamati et al., 2023)
Columns	Neural Networks	Concrete-Filled Tubular (CFT) Steel	(Al-Khaleefi et al., 2002)
Columns	Deep Neural Networks & ML Regressors	Polygon Section Concrete-Filled Steel Tube (CFST)	(Y. Chen et al., 2026)
Columns	Computational Model + ML	SFRC-Encased Light Gauge Steel	(Premkumar & Selvan, 2024)
Columns	Adaptive Sampling & ML Regressors	ECC / Concrete-Encased Steel (CES)	(Megahed, 2025)
Columns	Numerical & ML Modeling	GFRP-Confined Concrete-Steel Hollow Elliptical	(Isleem et al., 2024)
Beams	Explainable ML (XAI)	FRP-Strengthened Concrete	(Bhatt et al., 2025)
Beams	Genetic Evolutionary Deep Learning	FRP-Strengthened RC	(S. Wang et al., 2025)
Slabs	ANFIS (Fuzzy Logic)	Reinforced Concrete	(Bilgehan & Kurtoğlu, 2016)
Timber Panels	Simulation & ML	Cross-Laminated Timber (CLT)	(Schmid et al., 2018)

Structural Member Type	AI/ML Method	Material / Structural System	Source
Generic Members	Reduced-Order ML (Virtual Assistant)	Generic Structural Inference	(Naser, 2022)

As shown in Table 1, the literature demonstrates a broad investigation of ML techniques across diverse structural members. The dominance of column studies reflects both their structural importance and the relative abundance of legacy test data for this member type. Conversely, the appearance of timber and FRP-strengthened systems indicates a responsiveness within the research community to contemporary construction trends, such as the push for sustainable timber buildings and the need to evaluate retrofitting solutions in fire. The inclusion of a generic virtual assistant study (Naser, 2022) is particularly noteworthy, as it suggests a maturation of the field toward generalized tools that could potentially unify prediction tasks across different member types. It is also important to note the methodological breadth evident here: traditional neural networks coexist with advanced deep learning, fuzzy logic systems, and evolutionary optimization. This diversity indicates that no single algorithm has yet emerged as definitively superior for the fire resistance prediction task; rather, the choice of method often depends on the specific characteristics of the dataset (size, quality, feature dimensionality) and the desired interpretability of the model. The integration of explainability techniques, as seen in (Naser & Kodur, 2022), (M. Esteghamati et al., 2023), and (Bhatt et al., 2025), represents a critical step toward fostering trust in ML predictions for safety-critical applications such as structural fire engineering.

Post-Fire Damage Assessment and Residual Property Prediction

Following a fire event, the immediate and accurate assessment of structural damage and the quantification of residual mechanical properties are paramount for making informed decisions regarding rehabilitation, demolition, or safe reoccupation. Traditional methods for post-fire assessment rely heavily on visual inspection, non-destructive testing (e.g., ultrasonic pulse velocity), and core sampling, all of which are time-consuming, labor-intensive, and can provide only localized information. Machine learning offers a compelling paradigm shift by enabling the development of predictive models that can rapidly estimate the extent of damage and the residual capacity of structural materials from a set of easily measurable or known input parameters. The seven studies classified under this theme collectively explore this potential, focusing on both the macroscopic assessment of structural damage and the microscopic-to-macroscopic prediction of degraded material properties, primarily for concrete-based systems.

A significant cluster of research within this theme concentrates on the prediction of residual mechanical properties of concrete after exposure to high temperatures. The compressive strength of concrete, arguably the most critical property for structural integrity, is a primary target. For instance, a machine learning-driven framework was developed to predict the compressive strength of concrete containing waste powders after being subjected to elevated temperatures, demonstrating that the inclusion of waste materials does not preclude accurate post-fire strength estimation (Fathy et al., 2025). This study used a dataset compiled from experimental tests and trained several ML regressors, finding that ensemble methods such as gradient boosting provided superior predictive accuracy compared to single models. Expanding this concept to recycled materials, researchers applied experimental and machine learning-based analysis to investigate the influence of red mud on the properties of recycled aggregate concrete after fire exposure, where the ML model was used to map the complex interactions between mixture proportions, temperature exposure, and residual strength (Haider et al., 2025). The model's predictions aligned well with experimental observations, confirming that ML can handle the added variability introduced by unconventional aggregates.

Further advancing the prediction of residual concrete properties, a study specifically focused on the influence of aggregate type and size on the residual mechanical properties of post-heated geopolymer concrete (GHAZY et al., 2025). This investigation combined experimental testing with an artificial neural network (ANN) model to predict not only compressive strength but also other key properties like tensile strength and elastic modulus. The ANN was able to capture the distinct degradation patterns associated with different aggregates (e.g., basalt, limestone) and sizes, providing a nuanced tool for assessment that goes beyond simple strength prediction. Another work introduced an AI-driven quality classification framework for concrete after high-temperature exposure, moving beyond pure regression toward a hybrid assessment system (Kim & Lee, 2026). This framework first predicts the residual compressive strength using a machine learning model and then uses a second classifier to assign the concrete to a quality category (e.g., "no damage," "moderate damage," "severe damage") based on the predicted strength and other features. This hybrid approach is highly practical for field applications where a continuous strength value is less actionable than a categorical risk class.

A different but complementary line of inquiry within this theme concerns the structural-level assessment of damage and bond integrity. One study developed an interpretable machine learning framework for the rapid prediction of fire-induced structural damage at the building scale, going beyond material-level predictions (Chauhan et al., 2026). The framework was designed to assign a damage grade (e.g., light, moderate, severe, collapse) to entire structural systems based on inputs like fire duration, building geometry, and construction type. On the model interpretability front, this study employed explainable AI (XAI) tools such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to identify which features were most influential in driving the damage assessment, thereby increasing the model's transparency and trustworthiness for engineers. This work is particularly impactful because it directly addresses the practical need for post-fire triage and rehabilitation prioritization of urban structures.

Bond strength between steel reinforcement and concrete is another crucial property that degrades significantly after fire exposure, compromising the composite action that gives reinforced concrete its strength. A notable study directly addressed this by developing data-driven and explainable AI models specifically for evaluating the bond strength of reinforced concrete at elevated temperatures (Al-Hamd et al., 2025). The XAI analysis revealed that the maximum temperature exposure and the concrete compressive strength were the dominant predictors of residual bond strength, while the rebar diameter had a smaller but non-negligible effect. This insight is valuable for designing post-fire repair strategies, as it suggests that efforts to restore bond might need to focus on regions with small-diameter reinforcement or high concrete strength. Finally, the prediction of fire-induced concrete spalling in columns was the focus of a study that used AI to create a user-friendly fire assessment tool (Naser & Salehi, 2020). Spalling is a dangerous phenomenon where pieces of concrete break off from a column surface during heating, often exposing the reinforcement directly to fire. The ML model was trained on experimental data from fire resistance tests on RC columns to predict the likelihood and severity of spalling based on mix design parameters and fire exposure conditions. This tool allows engineers to screen concrete mix designs for spalling risk without costly testing, contributing to more resilient structural design.

To consolidate the diverse methodologies and objectives within this subsection, we present a comprehensive taxonomy in Table 2 below.

Table 2. Classification of studies on post-fire damage assessment and residual property prediction by analytical objective, specific property/system investigated, and AI/ML methodology.

Analytical Objective	Specific Property / System	AI/ML Methodology	Source(s)
Residual Material Property Prediction	Compressive Strength (Concrete w/ waste powders)	ML Regression (Gradient Boosting)	(Fathy et al., 2025)
Residual Material Property Prediction	Mechanical Properties (Geopolymer Concrete)	Artificial Neural Network (ANN)	(GHAZY et al., 2025)
Residual Material Property Prediction	Compressive Strength (Recycled Aggregate Concrete)	ML Regression	(Haider et al., 2025)
Damage Classification & Integrity Assessment	Quality Classification of Concrete	Hybrid ML: Regression + Classifier	(Kim & Lee, 2026)
Structural Damage Assessment	Building-Scale Damage Grade	Interpretable ML (SHAP, LIME)	(Chauhan et al., 2026)
Bond Integrity Assessment	Bond Strength (RC at Elevated Temp.)	Data-driven & Explainable AI (XAI)	(Al-Hamd et al., 2025)
Damage & Spalling Prediction	Concrete Spalling of Columns	ML Classification	(Naser & Salehi, 2020)

As illustrated in Table 2, the body of work in this area demonstrates a clear progression from simple material property regression toward more holistic and actionable assessment systems. The earlier studies (Fathy et al., 2025), (Haider et al., 2025), (GHAZY et al., 2025) are essential for establishing that ML models can accurately predict residual mechanical properties, which are the fundamental inputs for any structural analysis. However, their practical utility is limited without a broader context of structural behavior. The later studies address this gap by incorporating damage classification (Kim & Lee, 2026), bond integrity (Al-Hamd et al., 2025), structural-scale assessment (Chauhan et al., 2026), and specific failure mechanisms like spalling (Naser & Salehi, 2020). The integration of XAI methods in (Chauhan et al., 2026) and (Al-Hamd et al., 2025) is a particularly noteworthy development, as it moves the field beyond black-box predictions toward models that can explain *why* a certain damage grade or bond strength is predicted. This transparency is critical for building the trust of practicing engineers and code officials. The diversity of concrete systems studied, from conventional mixes to those incorporating waste powders (Fathy et al., 2025), red mud (Haider et al., 2025), and geopolymer binders (GHAZY et al., 2025), shows that AI/ML approaches are robust enough to handle the material variability that is a hallmark of sustainable construction. Future research in this theme should aim to integrate these material-level and structural-level assessments into a unified, end-to-end framework. Such a system could take as input a minimal set of observable features from a post-fire inspection (e.g., surface color, crack pattern, estimated peak temperature) and output a probabilistic assessment of the residual capacity of the entire structure, prioritized for rehabilitation. The foundation for this vision is being laid by the studies reviewed here, each contributing a critical piece of the puzzle.

Material Property Prediction Under Elevated Temperatures

A critical input for any structural fire resistance analysis, whether experimental, numerical, or data-driven, is the accurate characterization of material properties as they degrade under elevated temperatures. The thermal and mechanical response of construction materials at high temperatures is governed by a complex interplay of chemical reactions, phase changes, and microstructural evolution, making first-principles prediction exceedingly difficult. Consequently, there has been a substantial and sustained effort within the research community to apply AI and ML techniques to predict these temperature-dependent material properties. This subsection synthesizes the findings from 15 studies that fall under this thematic dimension. Our analysis reveals a clear concentration on concrete-based materials, with a secondary but significant focus on timber, polymers, and general building materials. The overall taxonomy of the studies is presented in Table 3, which hierarchically categorizes them by the primary material type, the specific predicted property, and the AI/ML methodology employed.

Table 3. Hierarchical categorization of studies on material property prediction under elevated temperatures, organized by material type, predicted property, and methodology.

Dimension (Material Type)	Material Sub-Type / System	Predicted Property	AI/ML Methodology	Source(s)
Concrete-Based	Standard & Fiber-Reinforced Concrete	Compressive Strength	Neural Networks & Ensemble Methods	(Ogunsaya & Taiwo, 2024), (Elshaarawy et al., 2024), (Mahmood et al., 2025), (Hasan et al., 2025), (Polo-Mendoza et al., 2024), (Oyebisi et al., 2025)
		Mechanical Properties (General)	Random Forest, Regression Models	(G. Chen et al., 2023), (Nas et al., 2026)
		Fire Performance & Spalling	Classification & Regression	(Ogunsaya & Taiwo, 2024), (G. Chen et al., 2023)
	Specialty & Blended Cement Concrete	Compressive Strength	Random Forest, XGBoost, SVM	(Sathiparan, 2024), (Oyebisi et al., 2025)
	Geopolymer & Alkali-Activated Materials	Mechanical Properties (General)	XGBoost, ANN, Combined ML	(Onyelowe et al., 2025), (Yilmaz et al., 2025)
		Rapid Chloride Permeability	ML Regressors, XAI	(Behera et al., 2025)
Timber-Based	Mass Timber	Charring Rate	Data-driven Methods (Regression)	(Amin et al., 2024)
Polymer & Composite	Electrospun Multilayer Materials	Fire Parameters (Self-extinguishing, Smoke Suppression)	ML Classification & Regression	(Bifulco et al., 2025)

Dimension (Material Type)	Material Sub-Type / System	Predicted Property	AI/ML Methodology	Source(s)
General / Cross-Cutting	General Construction Materials	Mechanical Properties	ANN, Deep Learning	(Hu et al., 2021)

The largest cluster of studies within this theme focuses on concrete, reflecting its dominance as a construction material and the critical need to understand its behavior in fire. A substantial body of work is dedicated to predicting the compressive strength of various concrete types at elevated temperatures. For instance, one study integrated machine learning and deep learning frameworks specifically to optimize material strength and fire resistance of concrete structures, demonstrating that algorithms such as random forests and deep neural networks can effectively map the relationship between mix design parameters (e.g., water-to-cement ratio, aggregate type, fiber content) and the resulting compressive strength after thermal exposure (Ogunsaya & Taiwo, 2024). This research was complemented by another investigation that developed an interactive graphical user interface (GUI) based on a trained machine learning model to predict concrete compressive strength, making the predictive tool accessible to practitioners without requiring programming expertise (Elshaarawy et al., 2024). The GUI approach represents a significant step toward bridging the gap between academic model development and practical engineering application.

Furthermore, the prediction of compressive strength has been extended to concrete incorporating supplementary cementitious materials and recycled aggregates, which are increasingly used for sustainability but introduce greater variability in high-temperature performance. For example, a study on high-strength glass powder concrete employed SHAP, PDP, and ICE explainability analyses to reveal how aggregate replacement ratio and temperature interact to influence strength, with the glass powder content identified as a critical parameter at elevated temperatures (Mahmood et al., 2025). Another investigation focused on hybrid-fiber-reinforced recycled aggregate concrete, using data-driven methods to predict compressive strength from features including fiber type, dosage, and temperature (Hasan et al., 2025). The model's accuracy demonstrated that machine learning can effectively capture the complex interactions between multiple fiber types and recycled aggregate quality. A broader computational model was also developed to estimate the engineering properties of Portland cement concrete (PCC) under various conditions, including thermal exposure, where the model was trained on a comprehensive database compiled from multiple experimental programs (Polo-Mendoza et al., 2024). Similarly, a study on blended cement concrete incorporating corncob ash and calcite powder adopted machine learning models to predict its mechanical strengths after heating, with the random forest algorithm showing the highest predictive fidelity (Oyebisi et al., 2025).

Beyond simple compressive strength, several studies have targeted a wider array of mechanical properties and performance metrics for concrete under elevated temperatures. One investigation evaluated the parameters of high-strength concrete and their interaction with raw material properties at elevated temperatures, emphasizing that the strength loss is not solely a function of temperature but also depends heavily on the original mix design and the nature of the aggregates (G. Chen et al., 2023). This study employed a machine learning framework to predict residual compressive strength, tensile strength, and elastic modulus simultaneously, treating them as a multi-output regression problem. Another research effort focused on basalt fiber composite mortars containing plastic waste and recycled aggregates, using an AI-based random forest regression model to predict their flexural and compressive strengths after fire exposure (Nas et al., 2026). This work is notable for extending ML prediction to composites that include both natural and synthetic waste fibers, a material system of growing practical interest. For specialty cementitious systems, a combined machine learning approach was used to predict the mechanical properties of self-compacting geopolymer concrete, comparing the suitability of different algorithms for this alkali-activated material (Onyelowe et al., 2025). Expanding on this, another study employed the XGBoost algorithm to predict the mechanical properties of geopolymer mortars, including those made with novel precursor combinations that lack extensive experimental data (Yilmaz et al., 2025). The model's robustness suggests that ML can serve as a reliable surrogate for initial material screening, which is particularly valuable when exploring new binder chemistries.

A third category of concrete-focused research addresses properties related to durability and fire performance that are indirectly linked to structural resistance. For example, the rapid chloride permeability of geopolymer concrete containing silica fume, fly ash, GGBS, and micro fibers was predicted using machine learning models, with the authors noting that synthetic fibers like polypropylene are preferred for fire resistance applications (Behera et al., 2025). While chloride permeability is primarily a durability metric, its prediction under high-temperature exposure provides insight into the material's pore structure evolution and potential for subsequent corrosion. Another study, focusing on prediction and validation of fire performance, developed ML models to predict the self-extinguishing and smoke suppression capabilities of electrospun PVP-based multilayer materials (Bifulco et al., 2025). This work broadens the scope of material property prediction to include not only structural load-bearing materials but also fire-protective coatings and barriers, which are integral to overall structural fire safety.

Finally, the prediction of material properties extends to timber-based structural systems. A study specifically addressed the prediction of the average charring rate of mass timber using data-driven methods for structural calculations (Amin et al., 2024). The charring rate is a fundamental parameter for determining the residual cross-sectional area of timber members in fire, and its accurate prediction is essential for the fire design of modern timber buildings. The study compiled a database of experimental charring tests and trained regression models, finding that the density and moisture content of the timber were the most influential predictors, beyond the standard assumption that charring rate is a function solely of the fire exposure time. This finding has direct implications for the fire design of timber structures, as it suggests that material characterization should be an integral part of the design process, not an afterthought.

A comprehensive mapping of all studies in this subsection, including those not explicitly represented in Table 3 due to space constraints, is provided below. The studies by (Ogunsaya & Taiwo, 2024), (Elshaarawy et al., 2024), (Mahmood et al., 2025), (Hasan et al., 2025), (Polo-Mendoza et al., 2024), and (Oyebisi et al., 2025) collectively establish that machine learning models can reliably predict the compressive strength of diverse concrete formulations under thermal exposure. The investigations by (G. Chen et al., 2023) and (Nas et al., 2026) expand the predictive scope to include multiple mechanical properties, while (Onyelowe et al., 2025) and (Yilmaz et al., 2025) demonstrate the adaptation of these techniques to geopolymer systems. The work on chloride permeability (Behera et al., 2025) and fire performance of polymers (Bifulco et al., 2025) further broadens the definition of relevant material properties. Finally, the study on timber charring (Amin et al., 2024) introduces a critical material property for an increasingly important structural material. Collectively, these studies illustrate that the application of AI and ML to material property prediction under elevated temperatures is a mature and highly productive subfield. The common thread across this body of work is the reliance on experimental databases that, while sometimes limited in size, are sufficient to train models that outperform conventional empirical equations in terms of accuracy and the ability to handle material variability. A notable gap, however, is the relative lack of attention to steel materials under elevated temperatures. Given that steel is a primary structural material in many buildings, and that its strength degradation follows a well-documented but mechanistically complex temperature-dependent curve, this represents a promising area for future research.

Explainable AI and Mechanistic Integration in Fire Engineering

The preceding sections have cataloged a wide array of successful applications of AI and ML to structural fire resistance prediction. However, a persistent criticism of many of these models is their "black-box" nature, which obscures the physical reasoning behind their predictions and consequently hinders their adoption in high-stakes engineering practice (Rudin, 2019). The need to transcend this limitation has given rise to a distinct and rapidly evolving subfield at the intersection of fire engineering and computer science: the development and application of Explainable Artificial Intelligence (XAI) and the integration of mechanistic knowledge into data-driven models. The eight studies categorized under this theme collectively grapple with the fundamental questions of how to make AI models transparent, how to discover causal relationships from fire test data, and whether the best path forward lies in creating interpretable models from the outset rather than explaining post-hoc approximations of complex ones.

A foundational debate within this subfield, and one that directly informs its application to fire engineering, concerns the philosophical and practical distinction between explainability and interpretability. One prominent argument posits that for high-stakes decisions, such as those in structural fire safety, interpretable models should be used directly rather than complex black-box models that are only later explained (Rudin, 2019). The proponent of this view contends that explanations of complex models can be misleading or unfaithful, and that inherently interpretable models, such as sparse linear models or decision trees with few leaves, provide a more reliable and verifiable basis for engineering judgments. This perspective is not without its counterarguments; for instance, a counterpoint emphasizes that the causal interpretation of model parameters is essential for true understanding, and that even inherently interpretable models can be misapplied if the underlying causal structure of the problem is not correctly specified (Naser, 2025). These broad methodological debates, while not immediately yielding a single correct approach, provide the essential philosophical scaffolding for the more applied work in fire engineering.

Within the specific domain of structural fire engineering, the concept of mechanistic integration has been formally articulated. Researchers have argued that the most promising path forward involves embedding physical knowledge directly into the architecture or training process of the ML model, thereby creating a "mechanistically informed" system that respects known physical laws while learning from data (Naser, 2021). This approach contrasts with a purely data-driven model that must infer all relationships from examples, or a purely physics-based model (like FEA) that is computationally expensive. A comprehensive review of the emergent role of XAI in the materials sciences has further contextualized these developments, highlighting how techniques like SHAP, LIME, and attention mechanisms are being used to validate model behavior and uncover hidden physical patterns in material datasets (Liu & Barnard, 2023). This review cross-pollinates ideas from the broader materials informatics community into the fire engineering domain, suggesting that the techniques developed for general material property prediction are directly applicable to the fire-specific problems explored in this review's previous sections.

The application of these XAI principles to fire engineering has yielded specific, actionable insights. For instance, explainable artificial intelligence has been employed to discover graphical heuristics for the fire-induced spalling of concrete (Tapeh & Naser, 2022). In this work, a decision tree model was trained on a dataset of fire tests on concrete columns, and the resulting tree structure, combined with SHAP analysis, revealed clear, interpretable rules governing spalling severity. The analysis showed that the combination of high moisture content, low permeability (often indicated by high compressive strength), and the presence of polypropylene fibers created the most pronounced spalling risks. These rules, which can be easily communicated to practitioners, represent a tangible outcome of XAI: a data-driven discovery translated into a simple, actionable heuristic. Similarly, the concept of revisiting "forgotten" fire tests through the lens of causal inference has been proposed as a powerful method for learning the idealized fire-induced response of RC columns (Naser & Çiftçioğlu, 2023). This study used counterfactual reasoning—asking "what would the response of this column have been if it had been exposed to a different fire scenario?"—to extract causal relationships from historical experimental data. The causal model robustly identified the fire resistance time and the steel reinforcement ratio as primary causal drivers of column failure, while controlling for confounding variables like concrete strength and aggregate type. This approach represents a significant methodological advancement, moving beyond mere correlation to infer causation, which is the gold standard for reliable engineering design.

The broader movement to "demystify" the concepts of black-box, white-box, and causal AI for fire scientists and engineers is captured in a synthesized review of "ten big ideas and rules" (Naser, 2022). This paper serves as a critical guide for the community, establishing a common vocabulary and set of principles for evaluating AI models. It distinguishes between:

- **Black-box models** (e.g., a deep neural network with millions of parameters), which provide high accuracy but no intrinsic explanation.
- **White-box models** (e.g., a small decision tree or a linear model), which are inherently interpretable but may have lower capacity.
- **Causal AI**, which explicitly models cause-and-effect relationships, enabling robust prediction under interventions (e.g., "what happens if we change the fire duration?").

The paper argues that for fire engineering, where the goal is often to predict the effect of a specific intervention (like adding a fireproofing material), causal models are conceptually superior to purely associational ones. Finally, the state of the art in XAI for structural design and assessment has been thoroughly reviewed, explicitly connecting the general principles to the challenges of fire prediction (M. Z. Esteghamati et al., 2026). This review found that, across all structural engineering applications, XAI methods are most commonly used for post-hoc model explanation, but their potential for model validation and discovery of new physical knowledge is only beginning to be tapped.

To provide a structured overview of these diverse contributions, we present a three-level taxonomy of the studies in Table 3.

Table 3. A three-level taxonomy of studies on explainable AI and mechanistic integration in fire engineering, categorized by main theme, sub-theme, and specific focus.

Main Theme	Sub-Theme	Specific Focus	Source(s)
Theoretical & Foundational Concepts	Fundamental Principles & Frameworks	Mechanistic Integration & Causal AI	(Naser, 2021), (Naser, 2022), (Naser, 2025)
		State-of-the-Art Reviews	(M. Z. Esteghamati et al., 2026), (Liu & Barnard, 2023)

Main Theme	Sub-Theme	Specific Focus	Source(s)
		Debate on Explainability vs. Interpretability	(Rudin, 2019)
Application in Fire Engineering	Prediction & Diagnosis	Fire-Induced Spalling of Concrete	(Tapeh & Naser, 2022)
		Fire-Induced Response of RC Columns	(Naser & Çiftçioğlu, 2023)
Methodological Approaches		Causal Inference & Counterfactuals	(Naser & Çiftçioğlu, 2023), (Naser, 2025)
		Graphical Heuristics & Rules	(Tapeh & Naser, 2022)
		Mechanistic Knowledge Integration	(Naser, 2021)

As Table 3 reveals, the literature in this subfield is not monolithic; it spans abstract philosophical debate, broad methodological reviews, and concrete applications. The studies by (Naser, 2021), (Naser, 2022), and (Naser, 2025) collectively establish the theoretical foundation, while the reviews (M. Z. Esteghamati et al., 2026) and (Liu & Barnard, 2023) provide comprehensive maps of the available tools and common practices. The applied works (Tapeh & Naser, 2022) and (Naser & Çiftçioğlu, 2023) demonstrate the practical power of XAI to generate new physical insights from legacy data. The debate initiated by (Rudin, 2019)—whether to use interpretable models from the start or to explain black-box ones—remains unresolved within the fire engineering literature, and its resolution may depend on the specific use case. For a code-based prescriptive check, a sparse decision tree might be ideal; for a complex failure analysis involving novel materials, a deep network with causal post-hoc analysis may be more appropriate. The key takeaway is that the fire engineering community is now actively and critically engaging with the issue of model transparency, a necessary step if AI and ML are to transition from academic research tools to trusted components of professional practice.

Advanced Composite and Strengthened Structures Analysis

The evaluation of fire resistance in advanced composite and strengthened structures presents a particularly demanding challenge due to the heterogeneous nature of these systems, the complex interaction between the substrate and the strengthening material at elevated temperatures, and the scarcity of experimental fire test data. Fiber-reinforced polymer (FRP) composites are increasingly employed for the retrofit and strengthening of existing reinforced concrete structures; however, the organic polymer matrix of FRP materials is highly susceptible to thermal degradation, softening at temperatures well below those encountered in a standard fire exposure. This vulnerability creates a multi-physics problem where the mechanical behavior of the retrofitted member is governed by the temperature-dependent properties of both the concrete and the FRP, as well as by the integrity of the bond interface between them. The seven studies synthesized under this thematic dimension collectively address this complexity by applying a diverse range of machine learning techniques to predict failure modes, load capacities, and bond strengths for FRP-strengthened and other composite systems under fire or high-temperature conditions. The overall taxonomy of these studies is presented in Table 4, which hierarchically categorizes them by the type of composite system, the primary mechanical response predicted, and the specific AI/ML methodology employed.

Table 4. Three-level taxonomy of studies on advanced composite and strengthened structures analysis, categorized by structural system, predicted response, and AI/ML methodology.

General Focus (Composite System)	Specific Structural Element / Phenomenon	Predicted Response / Property	AI/ML Methodology	Source(s)
FRP-Strengthened RC Beams	Flexural Behavior	Fire Resistance	Machine Learning (General)	(Bhatt et al., 2025)
		Fire Resistance	Genetic Evolutionary Deep Learning	(S. Wang et al., 2025)
		Flexural Capacity	Machine Learning Algorithms	(Khan et al., 2024)
	Shear Behavior	Shear Strength	Radial Basis Probabilistic Neural Network	(Abuodeh et al., 2020)
		Shear Strength	Physics-Guided XGBoost	(Singha et al., 2026)
FRP-to-Concrete Joints	Bond Interface	Interface Strength (NSM FRP)	Interpretable Artificial Neural Network	(M. Su et al., 2021)
Composite Materials (General)	Ablation & Performance	Ablation & Mechanical Properties	Five Machine Learning Models	(Karimi & Tousi, 2025)

The largest cluster of research within this theme is dedicated to the structural performance of FRP-strengthened reinforced concrete beams. The initial contributions in this area established the feasibility of using data-driven methods for a problem traditionally addressed through experimental furnace testing. For instance, a machine learning approach was developed to predict the fire resistance of FRP-strengthened concrete beams, demonstrating that input parameters such as beam geometry, concrete cover thickness, FRP type, and fire exposure duration could be mapped to a continuous fire resistance rating (Bhatt et al., 2025). This foundational work was significantly advanced by the application of a genetic evolutionary deep learning framework, which automatically optimized the architecture of a deep neural network to maximize predictive accuracy for the same fire resistance problem (S. Wang et al., 2025). The genetic algorithm evolved not only the network weights but also the number of layers and neurons per layer, resulting in a model that substantially outperformed standard neural networks and classical regression models. This study underscored the importance of automated architecture search for complex, multi-parameter problems where manual network design is often suboptimal.

Beyond pure fire resistance prediction, machine learning has been applied to predict the ultimate flexural capacity of FRP-strengthened RC beams, which is the load-carrying capacity at failure under ambient or fire-induced heating conditions, as a separate but related performance metric. An intelligent prediction modeling study used several ML algorithms, including support vector machines, random forests, and gradient boosting, to estimate the flexural capacity of such beams from a dataset compiled from experimental tests (Khan et al., 2024). The random forest model provided the best balance between accuracy and generalization, with a clear ranking of input feature importance that identified the area of FRP reinforcement and the effective depth of the section as the most influential parameters. This work provided a data-driven alternative to the empirical equations found in design codes, which are often calibrated to a narrow range of test data.

The shear behavior of FRP-strengthened RC beams, a failure mode that is often sudden and catastrophic, has also been a subject of intensive ML-based investigation. One of the earlier studies in this domain used a radial basis probabilistic neural network (RBPNN) to predict the shear strength of RC beams strengthened with externally bonded FRP sheets (Abuodeh et al., 2020). The RBPNN was chosen for its ability to handle sparse, noisy data, and the model successfully learned the non-linear interaction between shear span-to-depth ratio, concrete strength, and FRP reinforcement ratio. The probabilistic nature of the output also provided a measure of prediction uncertainty, which is valuable for reliability-based design. This stochastic approach was later complemented by a mechanism-aware, physics-guided XGBoost model for the same shear strength prediction task (Singha et al., 2026). The key innovation in this work was the explicit incorporation of a simplified physical model of shear transfer (the truss analogy) as a constraint during the training of the XGBoost ensemble. The model was penalized if its predictions deviated from the physically plausible bounds inferred from the truss model, thereby ensuring that the data-driven solution remained anchored in established mechanics. Explainable AI analyses using SHAP confirmed that the physics-guided model exhibited regime-dependent feature importance; for instance, the FRP contribution was identified as dominant in beams with low concrete strength, while the concrete contribution dominated in high-strength members. This study represents a state-of-the-art synthesis of data-driven learning and physical reasoning.

The integrity of the bond interface between the FRP and the concrete substrate is critical to the effectiveness of any strengthening system, particularly under fire where the polymer adhesive can soften. One investigation addressed this challenge by applying an interpretable artificial neural network to predict the interface strength of a near-surface mounted (NSM) FRP-to-concrete joint (M. Su et al., 2021). The NSM technique, where FRP bars or strips are inserted into grooves cut into the concrete cover, provides better fire protection than externally bonded FRP because the adhesive is shielded by the surrounding concrete. However, the bond behavior is still complex. The ANN model was made interpretable through a connection weight analysis, which identified the bond length and the concrete compressive strength as the dominant predictors of the ultimate bond force, while the groove dimensions had a secondary effect. This interpretability allowed the authors to validate that the model's sensitivity to physical parameters aligned with the known mechanics of NSM joints, increasing confidence in its predictive capability for scenarios not represented in the training data. A single study within this theme broadened the scope beyond purely structural elements to the material level, investigating the ablation and mechanical properties of a carbon/high silica/phenolic composite (Karimi & Tousi, 2025). This class of composite is used in high-temperature applications such as rocket nozzles and thermal protection systems, and its behavior under intense, short-duration heat flux (ablation) is distinct from the longer-duration, lower-intensity fire exposure of building structures. The study used five different machine learning models to correlate experimental data on ablation rates and mechanical property degradation with processing parameters and test conditions. The models successfully captured the non-linear effects of temperature and exposure time on the composite's mass loss and residual compressive strength, demonstrating that ML techniques are versatile enough to handle a broad spectrum of composite systems and thermal environments, even those far removed from conventional structural fire scenarios.

The studies by (Bhatt et al., 2025), (S. Wang et al., 2025), (Khan et al., 2024), (Abuodeh et al., 2020), (Singha et al., 2026), (M. Su et al., 2021), and (Karimi & Tousi, 2025) collectively establish that a wide range of AI/ML methodologies—from standard neural networks to evolutionary deep learning, physics-guided ensembles, and interpretable networks—can be successfully deployed for the analysis of advanced composite and strengthened structures under fire. The progression from general ML models to physics-guided frameworks is particularly clear in the sub-area of FRP-strengthened beams, where the shear strength prediction work demonstrates a maturation of the field toward greater physical fidelity. An important observation is that the focus of the included studies is heavily skewed toward FRP-strengthened RC beams. There is a notable lack of research applying similar advanced ML techniques to composite slabs (e.g., steel-concrete composite slabs), composite columns (e.g., FRP-confined concrete columns), or to the fire behavior of strengthened steel structures (e.g., steel beams retrofitted with FRP plates). These remain significant gaps, as the fire performance of such systems is often a governing design criterion and would benefit greatly from the predictive power of well-calibrated machine learning models. The integration of interpretability, as demonstrated in the NSM bond study (M. Su et al., 2021) and the physics-guided shear model (Singha et al., 2026), is a necessary condition for the broader acceptance of these tools by the structural fire engineering community for the design and assessment of strengthened structures.

Real-Time Response Forecasting and Simulation Surrogates

The practical application of structural fire engineering for performance-based design, real-time incident management, and post-event forensic analysis is often hampered by the prohibitive computational cost of high-fidelity finite element (FE) simulations. A single detailed FE analysis of a structure under a realistic fire scenario can take hours or even days to solve, rendering it unsuitable for tasks requiring rapid turnaround, such as parametric studies for design optimization or near-real-time predictions during a fire event. This computational bottleneck has motivated a distinct line of inquiry focused on developing AI and ML models that can serve as fast and accurate surrogates for expensive simulations. The six studies synthesized under this subsection collectively address the goal of real-time response forecasting and surrogate modeling, employing a range of strategies from direct FE-based learning to modular AI architectures and generative adversarial networks. A comprehensive taxonomy of these studies, organized by their primary goal, specific method, and implementation technique, is presented in Table 5.

Table 5. Three-level taxonomy of studies on real-time response forecasting and simulation surrogates, categorized by primary approach, specific goal, and technique.

Primary Approach	Specific Method / Goal	Technique / Implementation	Source(s)
Real-Time Response Forecasting	Direct Prediction of Structural Fire Response	Finite Element (FE)-based Machine Learning	(Ye et al., 2022)
	Modular Forecasting Frameworks	Modular AI for fire-induced structural responses	(Nan et al., 2023)
	Virtual Assistant for Reconstruction	Inference-based, simulation-free reduced-order model	(Naser, 2022)
Simulation Surrogates	Fire Resistance Classification via Synthetic Data	Generative Adversarial Networks (GANs) & AI Classifiers	(Çiftçioğlu & Naser, 2024)
	Prediction of Structural Component Behavior	Optuna-based ML optimization for strength/crack prediction in prestressed concrete	(Wen et al., 2026)
Domain-Specific Prediction (Surrogate with Physical Constraints)	Residual Stress Prediction in Welded Girders	Hybrid decoupled ML framework with physical constraints	(Zhang et al., 2026)

As Table 5 illustrates, the research in this area encompasses both general frameworks and domain-specific applications. The core idea of deploying a finite element-based machine learning approach for the real-time prediction of structural fire responses is a foundational concept, where a neural network or similar model is trained directly on a large dataset of FE simulation results to learn the mapping between input parameters and output response histories (Ye et al., 2022). This approach effectively distills the knowledge embedded in the FE solver into a compact, fast-executing model that can predict the entire time history of temperatures, deflections, and stresses for a given structural configuration and fire exposure, providing results in seconds rather than hours. The predictions from such a surrogate are not exact replicas of the FE results, but the errors are typically small enough for design and screening purposes.

A further refinement of this concept is the introduction of modular AI for forecasting fire-induced structural responses (Nan et al., 2023). Rather than using a single monolithic model to predict all outputs simultaneously, the modular framework decomposes the problem into independent, smaller sub-tasks, each handled by a specialized AI module. For example, one module might predict the temperature distribution through the cross-section of a steel beam, while another module, using the temperature output from the first, predicts the resulting thermal expansion and stress distribution, and a third module predicts the onset of buckling. This modular architecture offers several advantages: it is more interpretable, as each module corresponds to a distinct physical process; it is easier to train and validate, as each module has a simpler input-output mapping; and it is more maintainable, as individual modules can be updated or replaced without retraining the entire system. The results of this study demonstrated that the modular AI approach consistently delivered accurate forecasts of collapse times and failure modes across a range of structural configurations.

A more ambitious, generic framework was introduced in the form of a machine-learning virtual assistant for the accelerated, simulation-free, transparent, reduced-order, and inference-based reconstruction of the fire response of structural members (Naser, 2022). This work proposes a unified architecture that can take as input a minimal description of a structural member (e.g., material properties, cross-sectional dimensions, support conditions) and a fire scenario (e.g., the time-temperature curve from a standard fire or a parametric fire), and then, via a reduced-order model embedded within the virtual assistant, reconstruct the complete structural response without ever invoking a full FE simulation. The reduced-order model is constructed from a training dataset of pre-computed FE simulations, but the virtual assistant architecture allows it to generalize to new members and fires not explicitly present in the training data, albeit with a known and quantifiable uncertainty. The transparency of the virtual assistant is achieved through the use of physically interpretable internal parameters in the reduced-order model, and through the provision of confidence bounds on its predictions.

The generation of synthetic data to augment limited experimental datasets for model training is a powerful strategy, and this has been applied within the context of fire resistance evaluation. A study introduced a machine learning approach that uses generative adversarial networks (GANs) to create realistic synthetic fire test data, which are then used to train AI classifiers for evaluating the fire resistance of reinforced concrete (RC) structures (Çiftçioğlu & Naser, 2024). The GAN learns the underlying probability distribution of a set of real furnace test results and can then generate new, plausible samples of fire test data (e.g., temperature and deflection histories) that share the statistical properties of the real data. These synthetic data were used to train nine different AI classifiers to perform a binary classification task: "pass" or "fail" a given fire resistance criterion. The classifiers trained on the augmented dataset (real plus synthetic data) significantly outperformed those trained on the limited real data alone, achieving higher accuracy and robustness. This study demonstrates that GANs can effectively address the chronic data scarcity problem in structural fire engineering, enabling the application of sophisticated AI models even when only a few experimental tests are available.

While the aforementioned studies target general structural response, a more specific application of surrogate modeling is the prediction of behavior in prestressed concrete elements, which are widely used in bridge and parking structure construction. One study developed a machine learning model optimized with the Optuna hyperparameter optimization framework for the accurate prediction of strength and crack behavior in prestressed concrete beams (Wen et al., 2026). Optuna is a sophisticated, automated hyperparameter search algorithm that efficiently finds the optimal configuration of a machine learning model (e.g., the number of layers in a neural network, the learning rate, the regularization parameter) for a given dataset. The model, once optimized, could predict the ultimate load capacity and the crack width at service load for a prestressed concrete beam, given the geometry, prestressing force, and concrete strength. The predictive accuracy of the Optuna-optimized model was significantly better than that of a default model, demonstrating the critical importance of systematic hyperparameter tuning for achieving peak performance.

A related but distinct domain-specific application is the prediction of welding-induced residual stresses in steel girders, which can significantly affect the initiation of fire-induced buckling and structural collapse. A hybrid decoupled machine learning framework with physical constraints was developed for this task (Zhang et al., 2026). The welding process involves complex, coupled thermal and mechanical phenomena that are computationally expensive to simulate in full. The proposed framework separates the problem into a thermal stage (predicting the temperature history from the welding process) and a mechanical stage (predicting the resulting residual stresses from the temperature history), with each stage using a dedicated ML model. A critical innovation was the imposition of physical constraints on the ML model's output: for example, the predicted residual stress field was required to be self-equilibrating (the net force and moment across the cross-section must be zero), a fundamental law of mechanics. These physical constraints were enforced by penalizing the model during training if its predictions violated these equilibrium conditions, resulting in a surrogate model that was not only fast but also physically plausible. This hybrid, physics-constrained framework represents a powerful paradigm for creating trustworthy surrogates for complex thermomechanical processes in fire engineering.

The studies by (Ye et al., 2022), (Nan et al., 2023), (Naser, 2022), (Çiftçioğlu & Naser, 2024), (Wen et al., 2026), and (Zhang et al., 2026) collectively demonstrate a clear trajectory from simple FE-based surrogates toward more sophisticated, modular, and physically constrained frameworks. The modular approach (Nan et al., 2023) and the virtual assistant (Naser, 2022) emphasize architectural innovation for scalability and transparency, while the GAN-based data augmentation (Çiftçioğlu & Naser, 2024) tackles the fundamental data limitation problem. The domain-specific applications to prestressed beams (Wen et al., 2026) and welded girders (Zhang et al., 2026) show how these general principles can be tailored to specific structural components and manufacturing processes. A common thread across all these studies is the recognition that the surrogate model must not only be fast and accurate but also trustworthy, and the imposition of physical constraints (Zhang et al., 2026) and the use of modular architectures (Nan et al., 2023) are steps toward this goal. A significant gap in this sub-field is the lack of research on the real-time integration of surrogate models with sensor data from actual building fires. Such an online learning or data assimilation system would be able to update the surrogate model's predictions in real time as new data from sensors (e.g., thermocouples, strain gauges) become available, providing a continuously refining forecast of the structural response during a fire. This capability would be revolutionary for firefighter safety and incident command, but it remains largely unexplored in the current literature.

Broader Fire Safety Systems and Environmental Hazard Prediction

The scope of AI and ML applications in the domain of fire extends beyond the direct prediction of structural member resistance, encompassing broader fire safety systems and the prediction of environmental fire hazards. This subsection synthesizes a cluster of studies that examine how AI can enhance performance-based fire engineering design, detect and predict wildfire hazards, and forecast climate-related fire risk factors. While these studies may not directly predict the fire resistance of structural elements, they are integral to a holistic view of fire safety, as they influence fire behavior, detection, and environmental context, all of which affect the thermal exposure and, consequently, the structural fire resistance demand. The four studies classified under this theme collectively address topics ranging from indoor smoke motion prediction to large-scale wildfire detection and climate forecasting, representing the interface between AI-assisted structural fire engineering and the broader field of fire safety science. A comprehensive taxonomy of these studies, organized by their primary application domain, specific research objective, and technical methodology, is presented in Table 6.

Table 6. Two-level taxonomy of studies on broader fire safety systems and environmental hazard prediction, categorized by application domain and specific methodology.

Application Domain	Specific Research Objective	AI/ML Methodology	Source(s)
Building Fire Safety Systems	Prediction of smoke motion for performance-based design	Artificial Neural Networks (ANNs)	(L. Su et al., 2021)
Wildfire Detection & Prediction	Wildfire detection and prediction using IoT sensor data	Hybrid RF-XGBoost model (with SVM, KNN, XGBoost comparison)	(Radhi & Ibrahim, 2026)
Climate & Environmental Forecasting	Monthly climate prediction for fire risk assessment	Deep Convolutional Neural Network (CNN) & Long Short-Term Memory (LSTM)	(Guo et al., 2024)

The bridge between structural fire engineering and broader building fire safety is most clearly established through the application of AI to performance-based design (PBD) for predicting smoke motion. In modern performance-based fire engineering, the design of a structure's fire resistance is often predicated on the assumption of a specific design fire scenario, which includes the characteristics of the smoke layer and its heat release rate. This study introduced a smart framework for fire-engineering PBD to predict smoke motion via AI (L. Su et al., 2021). The authors constructed a computational fluid dynamics (CFD) database of visibility profiles in atrium fires, encompassing a wide range of fire scenarios, including varying fire sizes, locations, and atrium geometries. The AI model, based on an ANN, was then trained on this database to predict visibility distribution within the atrium as a function of the fire scenario parameters. The trained model could then be used by designers to rapidly evaluate the tenability conditions (based on visibility criteria) within a large, open-plan space without requiring a new, time-consuming CFD simulation for each design iteration. This work is critically important for structural fire resistance prediction because the fire's heat release rate and the smoke temperature profile directly influence the thermal loading on the structure. For example, if an AI model predicts rapid and deep smoke layer formation in an atrium, it implies a temperature gradient that could thermally charge the structural steel framing above the atrium, leading to potential overheating. Hence, the accurate prediction of smoke motion is a prerequisite for defining the thermal boundary conditions for subsequent structural fire analysis.

An entirely different but equally important application of AI in the fire safety domain is its use for the detection and prediction of wildfires. While this does not directly involve the built environment, wildfires represent a major environmental hazard that can directly threaten structures, leading to structural fire exposure that the models in previous subsections aim to predict. One study presented an intelligent IoT-machine learning framework specifically designed for early wildfire detection and prediction (Radhi & Ibrahim, 2026). The proposed system integrates data from a network of IoT sensors (e.g., monitoring temperature, humidity, wind speed, and gas concentrations) placed in forested areas. The core of the framework is a hybrid RF-XGBoost model, which combines the strengths of Random Forest (RF) for its robustness to outliers and feature interactions, and Extreme Gradient Boosting (XGBoost) for its predictive accuracy and handling of non-linear relationships. This hybrid model was benchmarked against several individual algorithms, including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and standard XGBoost. The results showed that the hybrid RF-

XGBoost model achieved the highest classification accuracy for detecting the onset of a wildfire. The implication for structural fire resistance prediction is indirect but significant: the earlier a wildfire is detected, the earlier predictions can be made regarding its potential impact on adjacent structures, allowing for timely defensive measures or evacuation. The data from such IoT wildfire monitoring systems could, in principle, be integrated with structural response models to provide near-real-time risk assessments for structures in the wildland-urban interface.

The final study in this subsection explores the use of deep learning for long-term climate prediction, specifically focusing on monthly climate variables that are crucial for assessing wildfire risk, such as temperature, precipitation, and drought indices (Guo et al., 2024). This study employed a combination of a deep Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network to forecast monthly climate patterns. The CNN component was used to extract spatial patterns from historical climate data, identifying features such as regional temperature anomalies and drought zones, while the LSTM component was used to capture the temporal dependencies, learning how past climate states influence future ones over seasonal timescales. The hybrid model's predictions of monthly climate variables were then used as inputs to established wildfire risk models to forecast periods of elevated fire danger several months in advance. For structural fire resistance prediction, the connection lies in the fact that long-term climate forecasts can inform the planning of fire-resilient infrastructure in regions prone to wildfires. For example, if a climate model predicts a series of hotter, drier summers, it justifies investments in enhanced passive fire protection (e.g., applying fire-resistant cladding, sprinkler systems) for structures in vulnerable zones. The ability to predict environmental fire hazard potential at a seasonal scale provides a strategic planning horizon that complements the more immediate warnings from wildfire detection systems.

The studies by (L. Su et al., 2021), (Radhi & Ibrahim, 2026), and (Guo et al., 2024) represent a diverse yet interconnected set of contributions. They collectively demonstrate that AI's role in fire safety is not confined to predicting structural element failure but extends to modeling the fire environment itself (smoke), detecting the fire hazard (wildfire), and forecasting the climatic conditions that drive that hazard (climate prediction). The integration of these three scales—building-scale smoke motion, landscape-scale wildfire detection, and global-scale climate prediction—is a promising direction for developing fully integrated, AI-driven fire risk management systems. For instance, such a system could use climate forecasts to identify high-risk regions, use IoT data for early wildfire detection in those regions, use AI smoke models to predict the thermal assault on the built environment, and then use the structural surrogate models reviewed in Section 3.7 to predict the response of the threatened structures. While such an integrated framework does not yet exist in the literature, the building blocks are being developed in the studies reviewed here.

Discussion

The body of literature synthesized in this review provides a comprehensive, albeit fragmented, map of how artificial intelligence and machine learning are being harnessed to address the long-standing challenges of structural fire resistance prediction. We did not merely observe a collection of isolated applications but rather a cohesive narrative emerging across the eight thematic dimensions, revealing a field that is progressing from proof-of-concept demonstrations toward more integrated, physically informed, and practically oriented tools.

A fundamental pattern that emerges across the studies is the consistent superiority of ensemble and deep learning methods over traditional regression or single-model approaches when sufficient, high-quality data are available. For instance, in the domain of fire resistance prediction of structural members, both the study on polygon section CFST columns using deep neural networks and ensemble regressors (Y. Chen et al., 2026) and the genetic evolutionary deep learning framework for FRP-strengthened beams (S. Wang et al., 2025) demonstrated that more complex, data-hungry models could capture the non-linear interactions between geometric, material, and fire exposure parameters that simpler models miss. This finding is mirrored in the material property prediction literature, where random forests (Elshaarawy et al., 2024) and XGBoost (Mahmood et al., 2025) consistently outperformed support vector machines and individual neural networks for predicting the compressive strength of concrete after thermal exposure. Taken together, these results suggest that the predictive ceiling for traditional, handcrafted models in this domain has been reached, and that further gains in accuracy will come from sophisticated architectural search, automated hyperparameter tuning as demonstrated by the Optuna framework (Wen et al., 2026), and the incorporation of physical constraints.

Simultaneously, we observe a conspicuous contradiction within the literature concerning the issue of data scarcity. Many studies, particularly those focused on advanced composite structures (Bhatt et al., 2025) and post-fire assessment (Fathy et al., 2025), explicitly acknowledge the severe limitations of available experimental datasets, often comprising fewer than 200 samples. Despite this, a majority of these same studies proceed to train and validate complex models with thousands of parameters, a practice that is statistically precarious and risks severe overfitting. The work on generative adversarial networks for synthetic data generation (Çiftçioğlu & Naser, 2024) directly confronts this contradiction, offering a methodological pathway to augment sparse experimental benchmarks with realistic, computer-generated samples. However, this approach itself has limits; the GAN's ability to generate physically plausible data is entirely contingent on the quality and representativeness of the initial training data. If the original experimental dataset is biased towards certain geometries or material types, the synthetic data will inherit and amplify these biases. Hence, the conflict between model complexity and data scarcity remains a central, unresolved tension in the field, one that calls for a more disciplined approach to model selection and validation, perhaps favoring simpler, more interpretable models for small datasets and reserving complex deep learning architectures for cases where either very large experimental databases or reliable simulation-derived datasets exist.

The implications of these synthesized findings for both theory and practice are profound. From a theoretical perspective, the growing body of work on explainable AI and mechanistic integration (Naser, 2021), (Tapeh & Naser, 2022), (Naser & Çiftçioğlu, 2023) challenges the traditional dichotomy in structural fire engineering between "empirical" and "physics-based" models. These hybrid approaches suggest that data-driven models, when stripped of their black-box mystique and instead constrained by physical laws or interpreted through causal analysis, can function as a third, epistemologically distinct class of model. They do not replace either experimental testing or FEA simulation; rather, they offer a way to efficiently distill knowledge from both sources into a compact, fast, and—crucially—transparent predictive tool. For practitioners, this means that AI models for predicting fire resistance are no longer merely academic curiosities. The development of interactive GUIs (Elshaarawy et al., 2024) and virtual assistants (Naser, 2022) directly addresses the accessibility barrier. A structural engineer in practice could, in the near future, use an AI surrogate to rapidly screen hundreds of design variants during the conceptual design phase of a building, reserving the more expensive FEA runs for the final verification of the few most promising configurations. Similarly, for post-fire damage assessment, the AI-driven quality classification framework for concrete (Kim & Lee, 2026) and the building-scale damage grade predictor (Chauhan et al., 2026) offer the potential to move beyond labor-intensive visual inspection toward a rapid, data-informed triage system that can prioritize inspection resources.

Nevertheless, our review methodology has inherent limitations that must temper the interpretation of these conclusions. The exclusion of non-English publications and grey literature, such as technical reports from government agencies like the National Institute of Standards and Technology (NIST) or the Building Research

Establishment (BRE), likely results in a publication bias toward academic studies that may over-represent novel algorithms and under-represent practical validation studies. Furthermore, our search strings, while comprehensive, rely on the authors' choice of keywords; a study on "surrogate modeling for fire-exposed steel frames" that never explicitly mentions "machine learning" in its title, abstract, or keywords would have been missed. The time frame of our search, while current up to September 2025, means that the very latest preprints and conference papers that push the field in new directions (e.g., the application of foundation models or large language models to structural fire problems) are not represented. Finally, the quality assessment of the included studies was based on peer-review status, not a systematic risk-of-bias assessment, meaning that some included models may have been trained on flawed data or validated with inappropriate metrics, leading to overly optimistic claims of performance that we were unable to critically evaluate within the scope of this review.

Based on these findings and limitations, several promising directions for future research become apparent. There is a pressing need for the establishment of open, standardized, and curated experimental benchmarks for structural fire resistance prediction. The current landscape consists of dozens of bespoke datasets, each with different variables, test protocols, and formats, making meaningful cross-model comparison impossible. A community-led initiative, similar to the UCI Machine Learning Repository or the benchmarks used in computer vision, would accelerate progress. Future research should also explore the integration of online learning and data assimilation into the surrogate modeling frameworks reviewed in Section 3.7. As demonstrated by the modular AI (Nan et al., 2023) and the virtual assistant (Naser, 2022), these surrogates can provide fast predictions, but they are static. A system that could update its predictions in real-time based on streaming sensor data from an instrumented structure during a fire would be transformative for firefighter safety and incident command. Understudied areas include the application of AI to full-scale structural systems (e.g., steel frames or complete buildings), as the majority of the literature focuses on isolated members. Furthermore, while polymer and composite systems have been explored (Bifulco et al., 2025), the application of advanced ML to predict the fire resistance of timber structures, particularly the novel engineered wood products like mass timber panels, remains limited relative to their growing market share. Finally, the theoretical debate between interpretability and explainability (Rudin, 2019), (Naser, 2025) needs to move from a philosophical discussion into a rigorous, empirical comparison within the context of fire engineering. Future work should explicitly compare the performance, trustworthiness, and practical utility of an inherently interpretable model (e.g., a sparse decision tree) against a complex deep network with post-hoc SHAP explanations for the same predictive task, to determine which approach actually yields more reliable and actionable insights for engineers.

Conclusion

We conducted this systematic literature review to map and synthesize the rapidly expanding body of research on AI and ML applications for structural fire resistance prediction. Our analysis of 56 peer-reviewed studies across eight thematic dimensions reveals that the field has moved decisively beyond isolated proof-of-concept demonstrations toward more sophisticated, integrated, and physically grounded approaches. Neural networks, ensemble methods, and deep learning architectures have become the dominant tools for predicting fire resistance of structural members, assessing post-fire damage, and modeling material degradation at elevated temperatures. The literature collectively confirms that data-driven models can capture complex, non-linear thermo-mechanical interactions with accuracy that often matches or exceeds traditional empirical methods, provided that sufficient high-quality training data are available.

The principal contribution of this synthesis lies in demonstrating that the field is undergoing a critical transition from purely correlational black-box modeling toward mechanistically informed and explainable frameworks. We identified a clear trajectory where physics-guided models, causal inference techniques, and XAI tools are being embedded into predictive systems to improve their trustworthiness and generalizability. These hybrid approaches challenge the conventional dichotomy between empirical and physics-based models, offering a pragmatically powerful third path that distills knowledge from both experimental testing and numerical simulation into fast, transparent surrogates. For practitioners, the emergence of accessible tools such as interactive GUIs, modular forecasting frameworks, and reduced-order virtual assistants suggests that AI-based prediction is becoming increasingly viable for routine engineering design and post-fire assessment, potentially transforming how fire resistance is evaluated in practice.

Nevertheless, significant barriers to widespread adoption remain. The chronic scarcity of large, standardized, and openly available experimental datasets continues to hinder model development and fair cross-method comparison. The tension between model complexity and data availability remains unresolved, demanding a more disciplined approach to model selection. Future research must prioritize the creation of community-curated benchmarks, the development of online learning systems that can assimilate real-time sensor data during fire events, and the extension of current methods to full-scale structural systems and emerging materials like mass timber. By addressing these gaps and building on the foundation of mechanistic interpretability established by the studies reviewed here, the field can move toward a future where AI-driven tools become trusted, integral components of structural fire safety engineering.

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