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# Advances in Polymer-Modified Concrete using XAI

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**_Abstract_**

*Industry 4.0 technologies are being quickly adopted by the construction sector, opening new avenues for enduring operational and environmental issues. This sector looks at how explainable AI can forecast air and enhance the quality of building materials. XAI, AI, ML, and big data drive a new paradigm in polymeric material development. The effective XAI and ML-assisted design creates innovative, high-performance polymeric materials. It covers building a database and representing structures, creating a model for predicting properties based on XAI and ML, creating a virtual design, and a high-throughput system. Training ML models that identify structure and material properties from available polymer data is essential because it makes it possible to ensure that promising polymers meet the desired property requirements. So, the main concern of this study is the use of XAI and machine learning to address these needs and their related problems. This study examines the use of XAI approaches in sustainable structural materials optimization in PMC and PCC to ensure that concrete construction projects for buildings have no adverse environmental effects. It describes various XAI-PMC models from 2021 to 2025 and compares them based on several parameters. Further, it provides analytical results based on these existing XAI-PMC models, including analysis on existing research contributions using XAI/AI techniques, year-wise research contributions and progress, and %usage of classifiers in existing XAI-PMC models*

**Keywords:** ML, XAI-PMC, compressive strength, industry innovation, sustainable economic growth, productivity growth, machining technologies, concrete technology, sustainable manufacturing

## INTRODUCTION

The science of effective, economical, and secure design [1] [2] in civil engineering projects leads to advanced concrete technology [7]. The smallest change in the project's conditions or goals is typically encountered by engineers and concrete designers, making it difficult to select the best design among multiple options [7]. Polymer-Modified Concrete (PMC), a cutting-edge building material, has superior adhesion, tensile strength, durability, and reduced vulnerability to chemical deterioration. Recent advances in eXplainable Artificial Intelligence (XAI), AI, and Machine Learning (ML) have demonstrated that among the domains of applicability of XAI, AI, and ML [1]–[6] is the prediction of compressive strength of PMC major input parameters [7]-[13] required to get an optimum mix design [21]. Other XAI Applications in different domains include medical imaging, natural language processing, and computer vision. Since the needs of various stakeholders vary, an increasing variety of explanation tools are being developed [14]-[18].

Although PMC is a viable substitute, it has issues using its resources to build strength. For it to be widely used as a sustainable material, these factors must be balanced. Compressive strength, setting time, and workability are all influenced by the type and dosage of precursors, activator, curing, and mixing circumstances [19] [20]. However, as the need for high-strength concrete for several uses grows, Polymer Concrete Composites (PCC)

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derived from industrial waste are gaining popularity [4]. PCC has distinct qualities, including great durability, reduced drying shrinkage, lower permeability, and chemical and heat resistance. The lack of new natural resources for building projects and the escalating climatic issues have shifted the research's focus toward sustainability. The idea of a circular economy has emerged as one of the most successful strategies for attaining long-term sustainability. Materials are often manufactured, used, and disposed of according to the traditional economic model.

Similarly, cement concrete has acceptable resistance in every environment [3]. The heat of hydration during the hardening process causes shrinkage and inner pores, which allow for a reduction in strength and durability. However, normal cement composites are not advised for deterioration processes in some conditions. In this case, certain additives are applied concretely to enhance their desired qualities and make them suitable for the surrounding environment. Polymers are well-matched additives in special situations where mechanical strength, water tightness, resistance, freezing and thawing, durability, corrosion resistance, and repairing old concrete structures are needed [3]. The properties of cementitious composites, in their fresh and hardened states, can be improved by SuperAbsorbent Polymer (SAP) [12]. It is crucial to understand that SAP concrete's strength could deteriorate. This reduction can be lessened by choosing the right kind of SAP and changing the composition of the concrete [12]. Fiber-Reinforced Polymers (FRP) have also received attention lately for Reinforced Concrete (RC) because of their remarkable qualities, which include stiffness, high specific strength, and lightweight design [20]. Structures, infrastructure, wind turbines, and other cutting-edge civil items have all used these qualities [20].

Furthermore, FRP materials are essential to several industries, including construction, infrastructure, automotive, and aerospace [11]. Although design criteria for FRP composites have been created, it takes a significant amount of time and resources to achieve the necessary strength of a FRP composite [11]. Because of its great strength, low cost, and convenient access to raw materials, ordinary cement mortar is frequently employed in construction engineering [14]. A popular and effective technique for designing and analyzing RC structures, the Strut-and-Tie Method (STM) is advantageous in areas with intricate stress distributions and discontinuities [17]. Despite recent developments in ML models, which are frequently employed as predictive models, it can be difficult to comprehend how input design parameters relate to the composite's output strength due to the model's intrinsic 'black box' character [11]. However, this ML-based design approach faces data and modeling challenges due to the lack of high-quality polymer data and the intricate polymeric multiscale material and structure–property correlations [13]. On the other hand, ordinary cement mortar has poor impermeability and considerable shrinkage, shortening the building's service life and producing a lot of carbon dioxide [14].

Because polymer additives improve cement mortar's mechanical qualities, researchers are becoming more interested in polymer cement mortar. Accurate concrete strength estimates assess building construction quality, which can cut labor expenses and construction time [15]. However, it takes a lot of time and money to produce them and to conduct the thorough testing needed to determine their viability. With the advent of Industry 4.0 and XAI, there are now chances to use ML techniques to overcome these limitations. Many XAI approaches have recently been employed to forecast the concrete properties and evaluate the significance of process factors for effective structural design and their wide uses [20]. Therefore, using XAI approaches to predict and optimize real-world concrete technology issues is an effective strategy.

The article is structured as follows. The next section discusses the PMC systems using XAI and AI-enabled techniques. It describes the basic working procedure of the XAI-PMC systems and the XAI techniques and tools. The following section explains a systematic and detailed review of the existing XAI-PMC systems, including their comparison and limitations. It compares various existing XAI-PMC models from 2021 to 2025, and compares existing models based on features, dataset, ML techniques, and performance. The next section provides the analytical results based on existing XAI-PMC models. The first analysis compares existing research contributions using XAI/AI techniques. The second analysis illustrates the year-wise research contributions and progress. The third analysis provides the %usage of classifiers in existing XAI-PMC models. The last section concludes the article with future recommendations.

**PMC SYSTEMS USING XAI AND AI-ENABLED TECHNIQUES**

XAI is a procedure and collection of techniques that help users interpret the output and outcomes produced by AI and ML techniques. It refers to a cluster of steps and methods that enable ML algorithms to generate results that are trustworthy, comprehensible, and interpretable for end users. Fig. 1 shows the working procedure of the XAI-PMC model. It follows the ML-based classification or prediction process and then applies the XAI to understand and interpret the data and results. Initially, this entire process sources the concrete data from different domains and cleans the gathered data. Further, it analyzes the features and trains the data to get various data points. Then it applies the XAI procedures at the junction point (or interface) of the PMC and PCC to gain insights into the data and functionality. Lastly, the PMC categorizations (classification / prediction / recommendation) are interpreted at the user level.

The main drawback of conventional ML models is their potential for bias and unfairness. These models can learn and encode biases in their predictions since they are trained on data that may be skewed, incomplete, or unrepresentative. This can compromise the impartiality and fairness of these models and result in unjust and discriminatory conclusions. These beginnings have resulted in diverse XAI techniques and strategies that offer significant advantages and insights across various fields and applications. XAI is commonly addressed concerning DL and is a crucial part of the Interpretability-Accountability-Transparency (IAT) ML paradigm. XAI techniques can be divided into two types, called Global XAI (GXAI) and Local XAI (LXAI). GXAI explains the model’s behavior on the entire data set and enables the general/usual/average behavior to be deduced. Conversely, LXAI refers to a single prediction for a particular client or user that the model works with. It typically displays which variables contribute to the model prediction and how. Figure 2 depicts the primary techniques and tools applicable in XAI-PMC, including SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), Skater, Explain Like I’m 5 (ELI5), Partial Dependence Plots (PDP) Box, and Shapash tool. Additional techniques include the tree surrogates, saliency maps, and rule-based models.

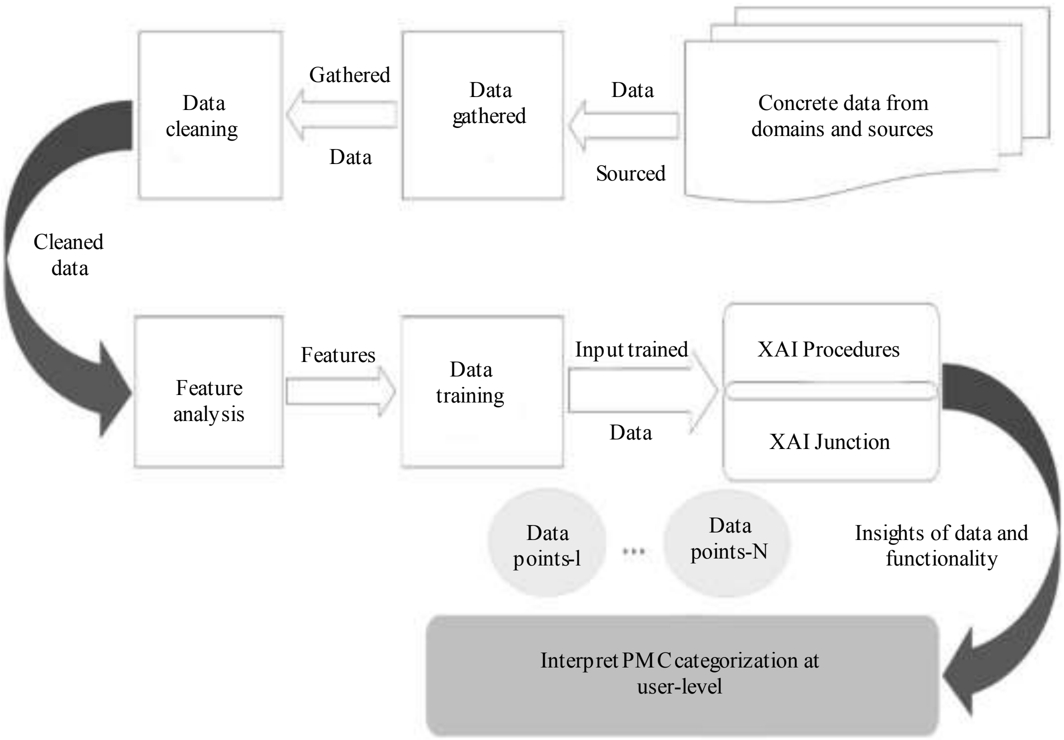


**Figure 1.** Depicting XAI-PMC working procedure.

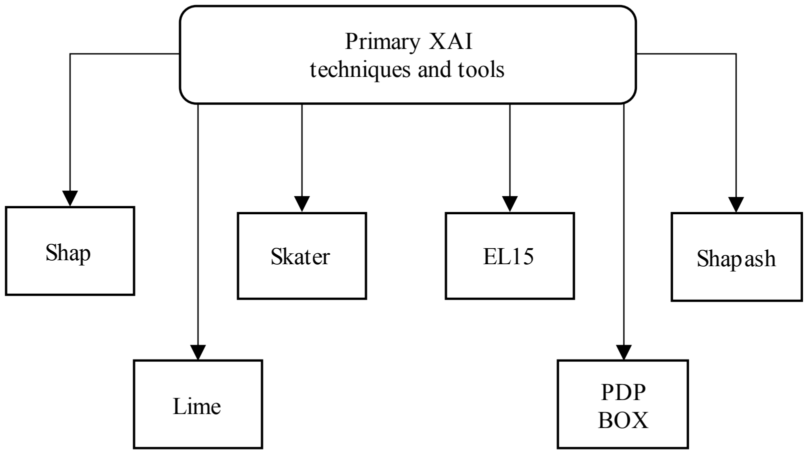

**Figure 2.** Primary techniques and tools in XAI.

First, SHAP uses the Shapley value from game theory to provide comprehensible and interpretable insights into the most relevant and significant elements in the model's predictions. Second, LIME employs a local approximation of the model to deliver interpretable and explicable insights into the most important aspects of the model's predictions. Third, Skater is a comprehensive explanatory method that creates a substitute decision tree model, aiding in understanding the prediction judgment process. Fourth, ELI5 offers interpretable and explicable insights into the model's predictions in an understandable language that even non-experts can grasp. It can be used with numerous AI algorithms to determine the permutational relevance for each prediction outcome. Fifthly, the PDP box outputs variations in the model's prediction caused by any variable. Sixth, the Shapash tool comprehends and explains ML models, assists with PMC and PCC models, and develops a web application that can benefit businessmen and end users. XAI techniques face numerous issues compared to previous transparency methods, including model performance, understanding and trust, training difficulties, a lack of standardization and interoperability, and privacy.

## LITERATURE REVIEW

Various existing PMC systems have used XAI and other ML techniques to discover the compressive strength of the construction materials. This review explains several XAI-PMC and ML-based PMC models from 2021 to 2025. These models have primarily predicted the compressive strength and mechanical properties of PMC for the construction industry, and many have provided an extensive review of their concerns. These models focused on the FRP composites, Aramid FRP Wraps (AFRPW), geopolymer-concrete production, Polymer-Modified Asphalt Binder (PMAB), Agro waste-derived geopolymer concrete, enhanced geopolymer concrete mix optimization, SAP, advanced polymeric materials, bibliometric-based Polymer Cement Mortar (PCM), and structural concrete members. They have been implemented with several XAI and ML-based techniques for PMC prediction, such as SHAP, Glycoluril, Generative Adversarial Networks (GAN), Graph Neural Network (GNN), Deep Neural Network (DNN), Support Vector Machine (SVM), Linear Regression (LR), Bagging Regression (BR), Random Forest Regressor (RFR), Extra Trees Regressor (ETR), AdaBoost, Gradient Boosting (GBoost), Extreme GBoost (XGBoost), Bayesian Optimization (BO), LightGBM, Decision Tree (DT), Random Forest (RF), and K-Nearest Neighbor (KNN). They are discussed below.

The research work [3] evaluated the mechanical features of concrete, such as compression, tension, and flexure, by adding glycoluril polymer. It evaluated the effects of polymer concrete and polymer dosage. It assessed the concrete mixes with 0%, 1%, 2%, 3%, and 4% glycoluril in 7 and 28 days. Another work [4] reviewed existing works to evaluate recycling and water utilization in the circular economy-based construction sector. It addresses the effects of polymer composites in concrete as supplementary cementitious materials with the production of polymer composites. It delves into a broad spectrum of polymers, examining their qualities, performance, and classification. Additionally, it explores various methods for producing polymer composites, aiming to identify the most suitable materials for specific applications. The approach in [5] applied AFRPW and GAN to predict the confined concrete, including strain and compressive strength. It worked on many features to measure the accuracy regarding the Coefficient of Determination ($R^2$), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). It used ETR, XGBoost, and KNN techniques for prediction.

Another review work [6] examined AI applications such as fuzzy logic, Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Gene Expression Programming (GEP), and other techniques in producing geopolymer concrete while analyzing the environmental impacts of concrete building constructions. Another study [7] reviewed the AI techniques for predicting and optimizing real-world problems in the concrete sector and checked the ten-year research trend. It was observed that some works performed scientometric analysis, and other works applied VOSviewer to use AI techniques and to identify the application scope. Next review [8] examined PMAB and discussed important factors such as swelling, storage stability, blend morphology, and the interactions within asphalt–polymer systems. Observations stated that PMAB was created by mixing elastomers, plastomers, and reactive polymers with virgin asphalt. It noted that thermoplastic elastomers and plastomers were the most used types of PMAB. Additionally, the review highlighted methods such as sulfur vulcanization, using antioxidants, incorporating hydrophobic clay minerals, functionalization, and the application of reactive polymers that could improve the compatibility between the polymer and asphalt.

Another model [9] applied SVM, BR, and RFR techniques to assess the mechanical strength of geopolymer concrete. The model was validated through statistical tests, $R^2$ metric, and absolute error assessment. The interaction graphs revealed that the mechanical characteristics of concrete incorporating corncob ash and slag were highly responsive to the mix proportions of ground granulated blast furnace slag, fine aggregate, and corncob ash. Another study [10] optimized the geopolymer concrete mix using XAI. SHAP interpretations identified temperature, Na to Al ratio, and NaOH molarity as key factors influencing compressive strength. This study evaluated the model's performance using the $R^2$ and RMSE. Three different kinds of datasets were used. The first dataset contained nine features, compressive strength was predicted using coarse aggregate, fine aggregate, NaOH, fly ash, ground granulated blast furnace slag, alccofine, $Na_2SiO_3$, and water. Pozzolana material, fly ash, molarity, Na/Si, Si/Al, $H_2O/Na_2O$, and Na/Al ratios were among the input variables for the second dataset's ten features that predicted compressive strength. The type-3 dataset, on the other hand, contained seven features, and had $Na_2SiO_3$, NaOH, the ratio of $Na_2SiO_3$/NaOH, molarity, curing temperature, and raised temperature input variables.

Another research work [11] provided insights into the model's input-output relationships and introduced a framework for XAI to enhance the FRP composite design. It utilized the SHAP and Partial Dependence Plots (PDPs). Additionally, it employed counterfactual techniques to adjust key design parameters, enabling designers to achieve the desired composite strength. Another method [12] suggested an ensemble learning-based prediction model for the deterioration of concrete's compressive strength that contains SAP [12]. The quality and accuracy of the results are significantly enhanced through the application of ensemble learning, demonstrating its superiority in merging multiple models to provide predictions with greater precision. It produced $R^2$ values of 0.90 and 0.88, where the ensemble model's MSE demonstrated better results. The strength reduction model was significantly influenced by the SAP%, SAP size, and compressive strength using SHAP. [13] discussed the state-of-the-art advancements concerning the ML-based design of polymeric materials. The digital representations of polymers for structure representation and database construction were the predominant methods in cheminformatics, along with newly developed techniques that integrated the polymeric multiscale structure characteristics. It selected the key and optimized the multi-fidelity ML models.

 

Another study [14] gathered and examined four hundred and twenty research papers in the field of PCM that were published between 1995 and 2023. This analysis included the keywords, co-citation of references, published journals, author cooperation networks, country cooperation networks, and publishing trends. The results showed a sharp and fine increase in publications between 2018 and 2023, with China leading the way in this area. The PCM research focused on mechanical characteristics, performance, hydration process, microstructure, and other associated elements. Recent research horizons included the application of SAP-modified PCM and polymer fiber in cement mortar, and the reinforcement effect of modified PCM on RC. Another work [15] introduced an interpretable framework to predict the compressive strength of concrete. It enhanced the accuracy of concrete strength prediction and determined optimal hyperparameters of the four ML models through 5-fold cross-validation and random search methods. It used the SHAP method to analyze the input feature's impact on the LightGBM prediction results.

Another method [16] analyzed the concrete properties by applying extreme fine-tuning and a DNN to predict the concrete compressive strength. It applied extensive hyperparameter optimization using XAI to establish causality in DNN results. Another study [17] reviewed the STM for modern RC design and analysis, focusing on shear-strengthened and continuous deep beams. It explored the integration of STM with computational tools and finite element analysis, investigating the real-world applications of STM, such as the design of bridge pier caps and complex regions. It highlighted the significance of STM in design optimization and its impact on the performance of RC structures.

Another study [18] assessed the ANN, SVM, whale, and moth flame optimization, AI, and ML models. These methods were evaluated for their capacity to enhance concrete quality, forecast air pollution levels, and track worker safety in real time. It was discovered that the researchers used $R^2$, RMSE, and MAE metrics to quantify the performance and forecast the compressive strength of materials such as cement mortar, fly ash, and stabilized clay soil. Furthermore, it was noted that AI has been used to forecast and lower air pollution emissions, including $PM_{2.5}$, $PM_{10}$, $NO_2$, CO, $SO_2$, and $O_3$. Monitoring health indicators like standing postures, electrocardiograms, and galvanic skin response enhances the quality of building materials and ensures worker safety. With an emphasis on Bangladesh, another study [19] examined the dynamics of PMC today and its prospects for the future. Its thorough examination of the recent developments in PMC technology emphasized the advantages of polymer modification, including enhanced durability, flexural strength, and resistance to environmental factors, including corrosion and chemical assault. Further, it discussed PMC applications utilized in ongoing building projects. It covered the potential and challenges of adopting PMC, including cost-effectiveness, availability of raw materials, and technological proficiency levels. It explored potential future research avenues, technological advancements, and legislative implications that could influence the widespread acceptance of PMC in Bangladesh. It also addressed the incorporation of recycled polymers, the optimization of mix design, and the development of consistent guidelines for PMC use in structures.

Another study thoroughly examined ML techniques to forecast the mechanical characteristics of FRP [20]. It assessed the performance of different models and extensively addressed their benefits and drawbacks. It identified the shortcomings of current research models and recommended enhancing their predictive accuracy for determining the mechanical characteristics of FRP components [20]. Another work [21] applied a hybrid technique of eight ML models to predict PMC compressive strength. It performed SHAP analysis to see how each feature affected predictions on the model outputs. It achieved significantly higher performance than conventional models. It performed the PDP analysis to interpret the contribution of individual inputs to the compression strength predictions.

**Comparison among Various Existing XAI-PMC Models: 2021-2025**

Table 1 compares the existing XAI-PMC techniques based on problem-focused and the target XAI or AI-based techniques. It is observed that most of the research contributions were published in the year 2024 and have been implemented with SHAP XAI.

 

**Table 1.** Comparing various existing models based on problem-focused and Use of XAI, AI, or PMC-based techniques.

| Reference no | Year | Problem-focused | Target XAI/AI technique |
|---|---|---|---|
| [3] | 2021 | Characterization of PMC strength | PMC-based |
| [4] | 2021 | Analysis and evaluation of recycling and waste management | PCC |
| [5] | 2023 | Predicting mechanical properties using AFRPW | SHAP and AFRPW |
| [6] | 2023 | Analyzing AI techniques for geopolymer-concrete production | AI-based |
| [7] | 2023 | Ten-year survey on advanced concrete technology | AI-based |
| [8] | 2023 | Detailed analysis on PMAB | PMAB |
| [9] | 2024 | Analyzing the strength parameters of geopolymer concrete constructed from agricultural waste | PMC |
| [10] | 2024 | Optimizing geopolymer concrete mix | SHAP |
| [11] | 2024 | FRP composite framework | SHAP |
| [12] | 2024 | Prediction of deterioration of concrete’s compressive strength using SAP | SHAP |
| [13] | 2024 | Advances in polymeric materials | Polymetric materials |
| [14] | 2024 | PCM development and bibliometric hotspot analysis | PCM |
| [15] | 2024 | Forecasting the compressive strength of high-performance concrete | SHAP |
| [16] | 2024 | Non-destructive prediction of concrete compressive strength | XAI |
| [17] | 2024 | STM developments and uses in RC | RC design |
| [18] | 2024 | Study on the construction sector revolution | SHAP |
| [19] | 2024 | Present and prospects of PMC in Bangladesh | PMC-Based |
| [20] | 2025 | Predicting the Performance of FRP-reinforced structural concrete members | SHAP |
| [21] | 2025 | Analyzing the mechanical strength of PMC | SHAP |

## Comparing Existing Models for Various Parameters

Table 2 compares existing techniques based on included features, datasets used, ML techniques applied, and achieved performance results. Many PMC and PCC models utilized diverse feature sets, including density, sorptivity, and acid resistance [3], mechanical properties [5] [9] [21], ply mechanical properties [11], and concrete properties [16]. Additional properties focused on in these models included polymer fingerprints and cross-linking descriptors [13], ash, water, cement ratio, slag, and water features [15], as well as other types of variables and features [10] [12]. Conversely, these models operated on various datasets, including the ply material dataset [11], multisource isomerous polymer data [13], concrete dataset [15], the concrete XAI dataset with 18,480 data points [16], and a 382-data-point dataset compiled from the literature [21]. Other datasets contained input parameters of 37 samples, 24 samples, and 28 samples [10]. Furthermore, various ML techniques implemented by these models include glycoluril [3], AFRPW [5], GAN [5], ETR [5], XGBoost [5] [11] [12] [15] [21], KNN [5] [21], SVM [9] [12] [21], BR [9] [21], RFR [9] [10], GBoost [11] [21], AdaBoost [15] [21], GNN [13], BO [13], RF [15], LightGBM [15], DNN [16], DT [21], and LR [21]. These models achieved promising results in increasing concrete strength [3]. Using various ML classifiers, they demonstrated $R^2$ values ranging from 57% to 98.7%.

**Table 2.** Comparing various existing models based on features, dataset, ML techniques, and performance.

| Reference no | Feature included | Dataset used | ML techniques applied | Performance results |
|---|---|---|---|---|
| [3] | Physical properties: density, sorptivity, and acid resistance. | Good dataset. | Glycoluril | 3% increase in the strength of concrete. |
| [5] | Mechanical properties. | Good dataset. | AFRPW, GAN, ETR, XGBoost, and KNN | $R^2$ = 98% |
| [9] | Mechanical properties. | 260 different datasets. | SVM, BR, and RFR | $R^2$ = 85%, and achieved high accuracy with SVM and BR. |
| [10] | 9, 10, and 7 features for 3 datasets in sequence. | 3 types of datasets. Input parameters: 37 samples (Type-1), 24 samples (Type-2), and 28 samples (Type-3). | RFR | Promising results. |
| [11] | 6 material characteristics as input features of the most influential ply material; Output: Maximum stress. | Ply material dataset | Ensemble of trees: GBoost and XGBoost | Promising accuracy results. |
| [12] | 10 distinct variables and the type of SAP. | Good dataset. | SVM and XGBoost | 91.02 % and 97.44 %, respectively, with 2 ML techniques. |
| [13] | Polymer fingerprints and cross-linking descriptors. | Multisource isomerous polymer data. | GNN and BO | Promising results. |
| [15] | Six features: ash, water/cement ratio, slag, and water features. | Concrete dataset. | RF, AdaBoost, XGBoost, and LightGBM | Promising results. |
| [16] | Concrete properties. | Concrete XAI dataset with 18,480 data points. | DNN | 98.7% accuracy in testing and validation. |
| [21] | Mechanical properties. | 382 data points compiled from the literature. | DT, SVM, KNN, BR, XGBoost, AdaBoost, LR, and GBoost | $R^2$ scores: 0.987 (training) and 0.577 (testing) with XGBoost and DT. |

**Limitations of Existing XAI-PMC-based Models**

This section focuses on the development directions and the present limitations and difficulties.

- Need to ensure compliance with regulatory standards in PCC [4]. Issues include minimum clinker concentrations [4], chemical characteristics of cement [4], data unavailability in the literature over the last 20 years [4], and the diversity of polymer concrete applications [4]. Need for more research to understand polymer concrete's behavior [4].
- Need extensive validation before applying in practical applications with large datasets [12] for ultimate strength and strain predictions [5]. Issue of missing values in the dataset and use of a small dataset [5]. Need to develop predictive models for rectangular columns [5].
- Need for further validation across diverse composite configurations and material systems [3] [10] [11] [13] [15] [16] [21].
- Need to make the model applicable to real-world scenarios [11].
- Need to mention the SAP size [12]. Need to study both cement paste and mortars separately [12]. Need to determine the SAP using an effective ML model.

 

- Need to improve the accuracy and performance results [3] [10] [13] [15] [16] [21].
- Need to improve the geopolymer concrete performance. [9]

If the inputs are enlarged, many models cannot work correctly since they can only take values from a restricted set of input variables. Second, it's likely that many of these models cannot work as expected if the data used to train them is very different from what they are meant to accomplish. How well the models predict the outcomes depends on how consistent or inconsistent the units of the input parameters are. Thirdly, the precise SAP size was only mentioned in a few investigations in some research work. Therefore, an efficient model must be proposed to boost the concrete's strength. Establishing innovative structure representation, XAI, and advanced ML modeling techniques for polymeric materials is desirable, especially when building huge models of polymers. Therefore, design methodologies aided by XAI and ML should be established to realize the invention of advanced polymeric materials.

## ANALYTICAL RESULTS BASED ON EXISTING XAI-PMC MODELS

Several PMC-based and PCC-based research contributions have been made using XAI, AI, and ML techniques in recent years. This section presents three different analyses to illustrate the participation of various existing research contributions and their findings in each of these analyses. Analysis I demonstrates the research contributions made using XAI, AI, and other techniques. Analysis II compares the year-wise research contributions and progress from 2021 to 2025. Analysis III describes the usage of different classifiers in the existing XAI-PMC models.

### Analysis I: Research contributions using XAI/AI Techniques

Figure 3 shows the research contributions made with XAI and AI techniques. It is observed that 47.36% of research work was contributed using SHAP or XAI techniques. Further, 10.52% of research was conducted with AI-based principles and methods. Lastly, 47.36% of contributions were made with other techniques, including PMC, PCM, PCC, AFRPW, PMAB, polymetric materials, and RC design.

### Analysis II: Year-Wise Research Contributions and Progress

Figure 4 illustrates the year-wise research contributions and progress of the existing XAI-PMC models. It is seen that 57.89% and 47.36% of research work were contributed in 2024 and 2023, respectively. In contrast, 10.52% of research works were published in each of 2021 and 2025. So, most of the research for PMC-based models was published in 2024.

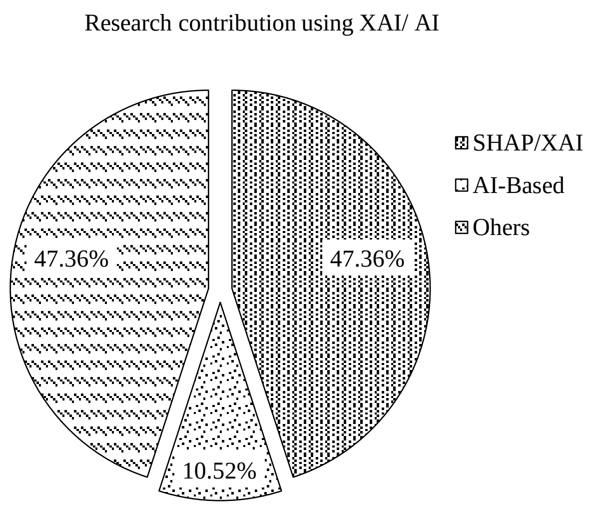


**Figure 3.** %Research contributions with XAI-AI techniques.

 

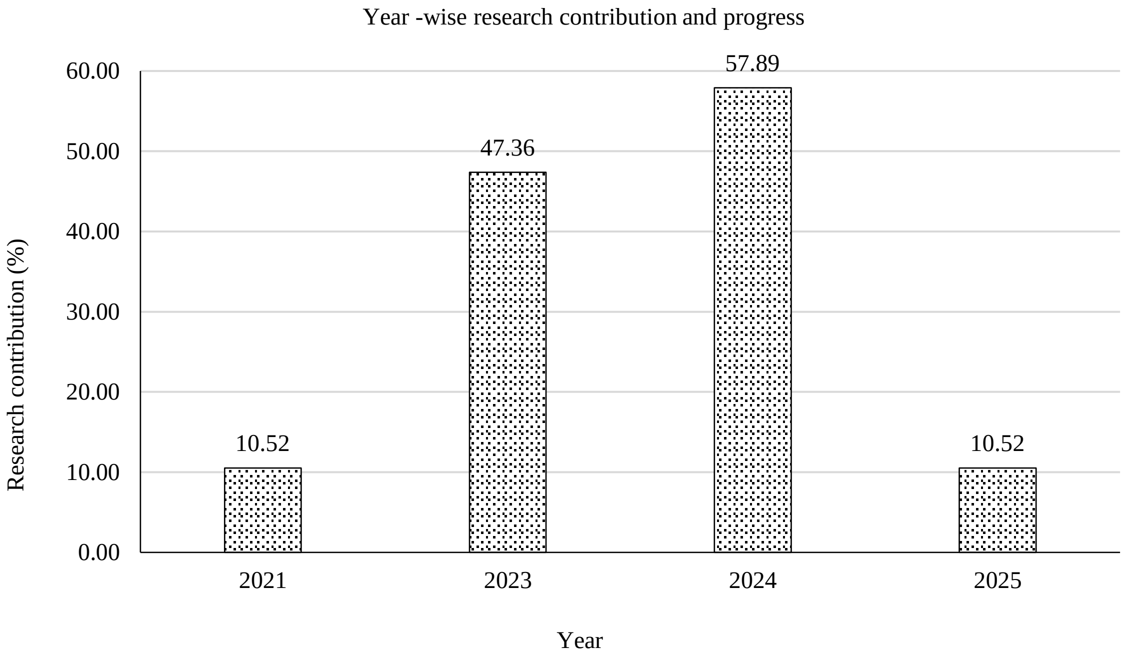


**Figure 4.** Depicting year-wise research contributions and progress in the existing XAI/AI-based models.

**Analysis III: %Usage of Classifiers in Existing XAI-PMC Models**

Figure 5 depicts the %usage of classifiers by the existing XAI-PMC models. It is observed that XGBoost was the most preferred classifier with 50% usage. The SVM classifier was applied by 30% of the research contributions. Apart from this, each of the KNN, BR, RFR, GBoost, and AdaBoost classifiers was used by 20% of research works. Lastly, each of the AFRPW, Glycoluril, GAN, ETR, GNN, BO, RF, LightGBM, DNN, DT, and LR classifiers was applied by 10% of researchers.

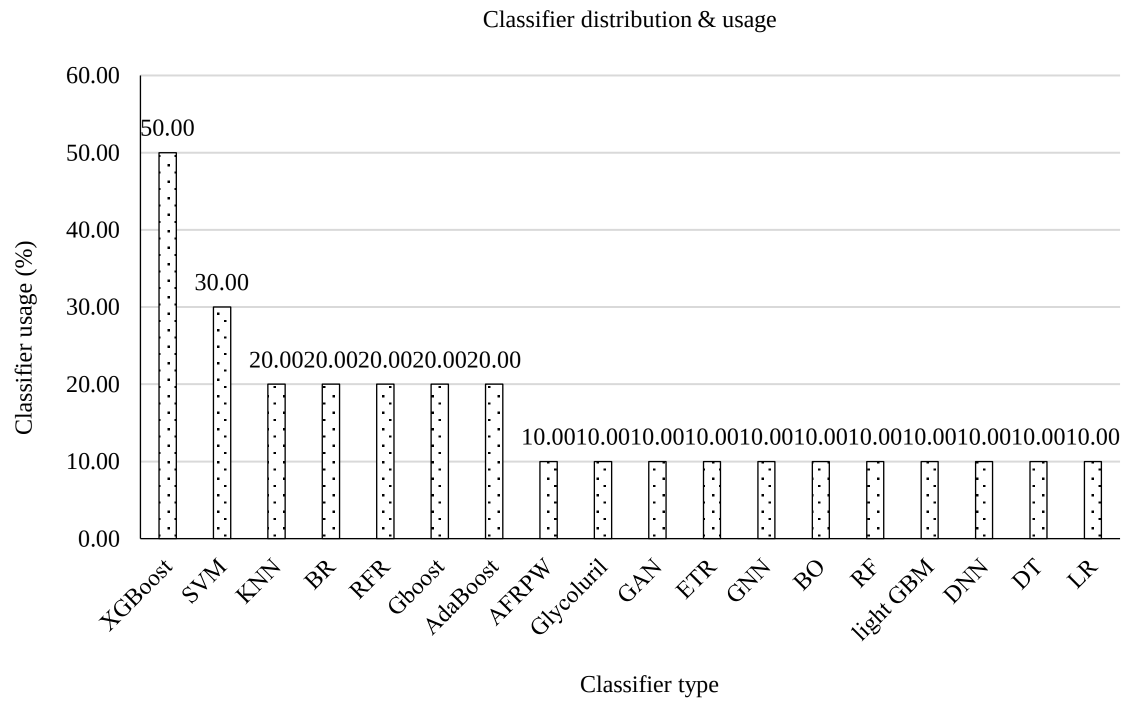


**Figure 5.** Classifier usage% in existing XAI-PMC models

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Therefore, the observations state that many research works have been proposed using XAI and AI-based techniques for PMC and PCC. Most of the research was published in 2024, and XGBoost was predominantly applied in many research works.

## CONCLUSIONS AND FUTURE RECOMMENDATIONS

The XAI-PMC study presented an analysis that focused on concrete characteristics, tackling several issues in the building industry. The most inventive and discerning materials are PMC. This work explored the use of XAI to comprehend the intricate links between the mechanical properties of concrete and its composition. It offered significant advancement in the non-destructive assessment of building materials. It established a new standard for XAI models' interpretability and transparency. This emphasis on explainability and accuracy marked a substantial breakthrough in using XAI as a potent tool in material science and civil engineering. It is determined that XAI technologies lead to improvements in the building sector. According to the models' performance criteria, real-time construction processes are good. This study emphasized the versatility and efficiency of these technologies in addressing present and future construction demands. There are still gaps in several research areas, like the utilization of huge datasets, deeper XAI integration across various building contexts, and the requirement for additional model validation in practical applications. Lastly, this study demonstrated how XAI and ML can completely transform the construction sector by encouraging sustainable practices and enhancing operational efficiency. For industry stakeholders interested in implementing XAI technology, this research can be expanded to provide insightful information.

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## REFERENCES

1. Puri S, Singh SP. Advanced applications on bilingual document analysis and processing systems. International Journal of Applied Metaheuristic Computing. 2020; 11(4): 149-93p.
2. Puri S, Singh SP. A fuzzy matching based image classification system for printed and handwritten text documents. Journal of Information Technology Research. 2020; 13(2): 155-94p.
3. Pothinathan S, Muthukannan M, Selvapalam N, et al. Investigation on strength properties of polymer modified concrete using glycoluril. International Review of Applied Sciences and Engineering. 2021; 12(3): 278-84p.
4. Alhazmi H, Shah SAR, Anwar MK, et al. Utilization of polymer concrete composites for a circular economy: A comparative review for assessment of recycling and waste utilization. Polymers. 2021; 13(13): 1-39p.
5. Cakiroglu C. Explainable data-driven ensemble learning models for the mechanical properties prediction of concrete confined by aramid fiber-reinforced polymer wraps using generative adversarial networks. Applied Sciences. 2023; 13(21): 1-22p.
6. Alaneme GU, Olonade KA, Esenogho E. Critical review on the application of artificial intelligence techniques in the production of geopolymer-concrete. SN Applied Sciences. 2023; 5(217): 1-25p.
7. Kazemi R. Artificial intelligence techniques in advanced concrete technology: A comprehensive survey on 10 years research trend. Engineering Reports. 2023; 5(9): 1-71p.
8. Emtiaz M, Imtiyaz MN, Majumder M, et al. A comprehensive literature review on polymer-modified asphalt binder. CivilEng. 2023; 4(3): 901-32p.
9. Al-Naghi AAA, Amin MN, Khan SA, et al. Modeling the strength parameters of agro waste-derived geopolymer concrete using advanced machine intelligence techniques. Reviews on Advanced Materials Science. 2024; 63(1): 1-18p.
10. Revathi B, Gobinath R, Bala GS, et al. Harnessing explainable Artificial Intelligence (XAI) for enhanced geopolymer concrete mix optimization. Results in Engineering. 2024; 24: 1-12p.
11. Yossef M, Noureldin M, Alqabbany A. Explainable artificial intelligence framework for FRP composites design. Composite Structures. 2024; 341: 1-13p.

12. Hosseinzadeh M, Mousavi S, Dehestani M. An ensemble learning-based prediction model for the compressive strength degradation of concrete containing superabsorbent polymers (SAP). Scientific Reports. 2024; 14: 1-21p.
13. Gao L, Lin J, Wang L, et al. Machine learning-assisted design of advanced polymeric materials. Accounts of Materials Research. 2024; 5(5): 571-84p.
14. Peng W, Fei W, Mingquan M. The research progress and hotspot analysis of polymer cement mortar based on bibliometrics. Frontiers in Materials. 2024; 11: 1-15p.
15. Zhang Y, Ren W, Chen Y, et al. Predicting the compressive strength of high-performance concrete using an interpretable machine learning model. Scientific Reports. 2024; 14: 1-18p.
16. Guzmán-Torres JA, Domínguez-Mota FJ, Tinoco-Guerrero G, et al. Extreme fine-tuning and explainable AI model for non-destructive prediction of concrete compressive strength, the case of ConcreteXAI dataset. Advances in Engineering Software. 2024; 192.
17. Kalantari SM, Kianoush MR. Advances and applications of the strut-and-tie method in reinforced concrete design: A state-of-the-art review. Structures. 2024; 69: 1-28p.
18. Gill EZ, Cardone D, Amelio A. Revolutionizing the construction industry by cutting edge artificial intelligence approaches: A review. Frontiers in Artificial Intelligence. 2024; 7: 1-20p.
19. Ahmmed MM, Puri S. Current trends and future trajectories: Polymer-modified concrete in the context of Bangladesh. Journal of Polymer & Composites, STM Journals. 2024; 12(SI2): 285-94p.
20. Kazemi F, Asgarkhani N, Shafighfard T, et al. Machine-learning methods for estimating performance of structural concrete members reinforced with fiber-reinforced polymers. Archives of Computational Methods in Engineering. 2025; 32: 571–603p.
21. Sobuz MHR, Khatun M, Kabbo MKI, et al. An explainable machine learning model for encompassing the mechanical strength of polymer-modified concrete. Asian Journal of Civil Engineering. 2025; 26: 931–54p.

 