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A Data-Driven Investigation of Factors Influencing Compressive Strength in Ultra-High-Performance Concrete

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ABSTRACT

Ultra-high-performance concrete (UHPC) exhibits exceptional mechanical performance, durability, and long-term serviceability; however, its compressive strength is governed by numerous interacting mixture-design and curing variables. Conventional experimental optimization is often time-consuming and resource-intensive, creating a need for interpretable data-driven approaches capable of supporting material design and performance prediction. This study investigated the factors influencing UHPC compressive strength and developed a predictive framework for identifying the dominant variables affecting strength development. A cleaned secondary dataset containing 626 UHPC mixtures, 24 predictor variables, and one compressive-strength target variable was analyzed. Exploratory analysis and Pearson correlation were used to examine variable relationships. A Random Forest regression model was developed using an 80:20 train-test split and evaluated using the coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), and five-fold cross-validation. Feature importance and partial dependence analyses were subsequently employed to interpret the contribution of individual variables. The Random Forest model achieved strong predictive performance, with a test R^2 of 0.9041, MAE of 7.79 MPa, RMSE of 11.09 MPa, and a mean five-fold cross-validation R^2 of 0.9178. Curing time emerged as the most influential variable, contributing 57.4% of the total feature importance. Sand content showed the strongest negative influence, while silica fume content, cement content, steel fiber content, and superplasticizer content also contributed to prediction accuracy. The findings demonstrate that interpretable machine learning can accurately predict UHPC compressive strength while revealing the relative influence of key mixture-design variables, providing useful guidance for future UHPC design and optimization.

1. Introduction

Ultra-high-performance concrete (UHPC) is one of the most developed cement-based construction materials that has high mechanical strength, durability and promising long-term properties in extreme service conditions. UHPC has much higher compressive strength, lower permeability, and a higher resistance to environmental degradation than traditional concrete, and these properties make UHPC ideal for use in critical infrastructure projects, including bridges, high-rise buildings, offshore structures, and transportation networks (Xue et al., 2020). The benefits of UHPC, such as enhancing structural longevity and lowering maintenance costs and overall lifecycle expenses, are driving its increasing use in contemporary construction. Due to the exposure of infrastructure systems under an aggressive environment, durability is becoming more critical, and UHPC has demonstrated a strong ability to resist chloride penetration, freeze-thaw cycles, abrasion and chemical attack (Li et al., 2020). Caringly designed mixture proportions that feature optimized particle packing, low water-to-binder ratio, quality cementitious materials and advanced chemical admixtures are the key to the superior performance of UHPC. Use of supplementary cementitious materials (SCM) like silica fume, fly ash, and slag is important for the densification of the matrix and mechanical properties of concrete and for enhancing sustainability by partial replacement of cement (Park et al., 2021). The resultant microstructure possesses a very compact matrix with low porosity and a strong bond between the matrix and the particles, all of which combined give UHPC excellent strength and durability (Bahmani & Mostofinejad, 2022). Recent advances have also been made in the use of UHPC with the incorporation of other binders and environmentally friendly constituents, paving the way for the consideration of both mechanical properties and environmental factors in the design of UHPC materials (Abdellatief et al., 2023).

Although these benefits exist, the compressive strength of UHPC is extremely susceptible to many parameters of the mixture design and cure process. The composition of the binder, properties of the aggregates, fiber reinforcement, curing conditions and specimen geometry can have significant effects on strength development. The ratio of water/binder is regarded as one of the most important parameters that affects the hydration kinetics, the refinement of pores and the mechanical properties (Mu et al., 2025). Because of the number of interacting variables in the design of UHPC, it becomes difficult to use the traditional experimental method, which might require a lot of laboratory testing and resources to consider a series of mixture combinations.

With the growing number of material datasets, new data-driven tools that can accelerate materials development and optimization have been developed. The data-driven materials science approach can deliver insights from the massive amount of data, find hidden patterns, and facilitate better decision making, compared to the traditional trial-and-error experimental method (Wang et al., 2022). Machine learning (ML) has received significant focus in the concrete technology area as a tool for predicting concrete properties and optimizing designs. Predictive methods of concrete compressive strength that employ machine learning algorithms such as adaptive boosting, support vector regression, k-nearest neighbors, and others have shown good prediction for the input variables of the concrete mixtures (Feng et al., 2020). Likewise, in comparative studies, it has been demonstrated that the strength of materials can be well modeled by advanced machine learning techniques, while maintaining high predictive accuracy, even for nonlinear material relationships (Beskopylny et al., 2022).

In recent years, the use of machine learning in UHPC has grown by a large margin. Existing reviews show that the use of machine learning methods to predict mechanical properties, optimize mixture proportioning, and assess the performance of UHPC at various scales is becoming prevalent (Teoh et al., 2026). Data-driven methods have also been used for estimating compressive strength and implementing mixture optimization strategies for better performance and resource efficiency (Bu et al., 2025). In addition, recent critical reviews have pointed out the importance of soft computing techniques in the prediction of the mechanical behavior of high-performance and ultra-high-performance concretes, where they can be used to complement experimental methods (Kumar et al., 2025).

While some previous machine learning studies have proved the feasibility of predicting the properties of concrete and UHPC, most of the existing research is mainly focused on the maximization of

prediction accuracy and the performance of algorithms. Much less has been written about understanding the relative influence of individual mixture design variables and interpreting the influence of the variables on compressive strength development. Thus, research is still needed on predictive models and analytical approaches that include interpretability to identify the most important factors that influence the strength performance of UHPC.
To address this need, the present study uses a data-driven framework to analyse the factors affecting the compressive strength of UHPC. A Random Forest model was built to forecast the compressive strength from the variables that were involved in the mixture design; the correlation analysis, feature importance analysis and partial dependence analysis were used to find and understand the most important predictors. The study combines predictive modeling with interpretable machine learning techniques, shedding light on the factors that most significantly affect the strength development of UHPC, and also providing valuable insights that could help inform future mixture design and optimization research.

2. Methodology

2.1 Research Design

In this study, quantitative research design and data-driven research were used to reveal the factors that affect the strength of UHPC. The secondary data was processed with statistical methods and a Random Forest regression model to detect the interrelationship between the variables, predict the compressive strength and determine the most important predictors.

2.2 Data Source

This study relied on publicly available data from Mahjoubi (2021) to create a dataset. The data set includes experimentally obtained observations of the UHPC mixtures and material properties. In the current research, the compressive strength subset is chosen because it is an important indicator of the mechanical properties of UHPC (Mahjoubi, 2021). After preprocessing, the data set had 626 observations, 24 predictor variables and one target variable, which was compressive strength.

2.3 Data Preparation

All the variables were coded into numeric form, and a data quality check was carried out to clean up missing data and duplicate records. There were no missing data values or duplicate observations in the final data set. All analyses were then conducted on the cleaned data set.

2.4 Exploratory Data Analysis

The exploratory data analysis was performed to investigate the data set. Descriptive statistics were computed to describe the distribution of the compressive strength. Pearson correlation analysis was then used to assess the correlation of the predictor variables with compressive strength and to determine which variables are most closely associated with compressive strength.

2.5 Random Forest Model Development

The predictor variables were used to develop a Random Forest regression model to predict the compressive strength. The dataset consisted of an 80:20 training and testing subset. The model was built with 300 decision trees and a fixed random seed to guarantee the model's repeatability.

2.6 Model Evaluation

The performance of the model was assessed by the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). These metrics are based on the test set. Five-fold cross-validation was employed to evaluate the robustness of the model. The model stability and generalization capacity were assessed based on the average R^2 value calculated over the validation folds.

2.7 Feature Importance and Partial Dependence Analysis

The trained Random Forest model was used for feature importance analysis to assess the relative contribution of predictor variables to the prediction of compressive strength. The variables were ranked based on their importance scores. Partial dependence analysis was then used to investigate the effects of the two variables most influential on the prediction of the compressive strength, while holding the other variables constant.

3. Results

3.1 Distribution Characteristics of UHPC Compressive Strength

After cleaning and preprocessing the data, a total of 626 UHPC mixtures were analyzed. There were 24 variables in the dataset, including variables that describe the characteristics of the mixtures designed, and one target variable that describes the compressive strength. Compressive strength values ranged from 16.8 MPa to 217.0 MPa, with the average value of 112.6 MPa and the median of 114.0 MPa. The variability among the investigated mixtures is relatively high, as demonstrated by the high standard deviation of 34.8 MPa, which indicates the material composition and curing conditions of the investigated range. The frequency distribution of compressive strength values is plotted in Figure 1. The majority of mixtures were found to be high strength, and most observations were focused on this range (90MPa to 150MPa). The near symmetry around the median and mean values confirms that the distribution is fairly symmetric, and the number of low and high-strength mixtures shows that the performance range of the data set is quite wide. This variability gives an appropriate option to study the effect of mixture-design variables on the compressive strength.

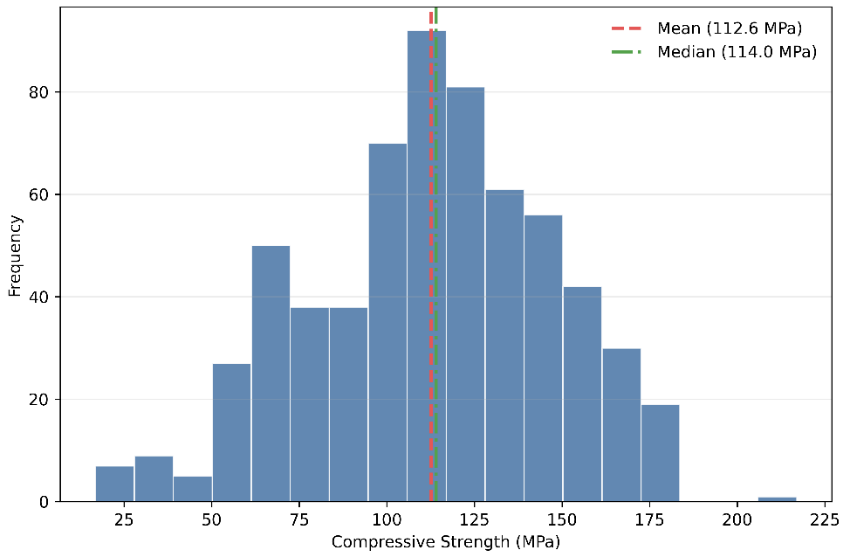

Figure 1. Distribution of UHPC compressive strength

3.2 Relationship Between Input Variables and Compressive Strength

The Pearson correlation test was used to find the variables that most strongly correlated with the compressive strength. From the results of the correlation analysis shown in Figure 2, it can be seen that the most significant positive correlation with curing time is compressive strength ($r = 0.397$), followed by maximum aggregate size ($r = 0.319$), coarse aggregate content ($r = 0.302$), cement strength class ($r = 0.272$), and cement compressive strength ($r = 0.224$). Both curing-related factors and aggregate properties are beneficial for the development of strength, as the above results show. Sand content, on the other hand, exhibited the highest negative correlation with compressive strength ($r = -0.346$), while the correlation for water content ($r = -0.180$) and specimen length ($r = -0.157$) were also negative. The relatively low magnitudes of the observed correlations indicated that compressive strength development is the result of several interacting variables instead of a single dominant linear variable.

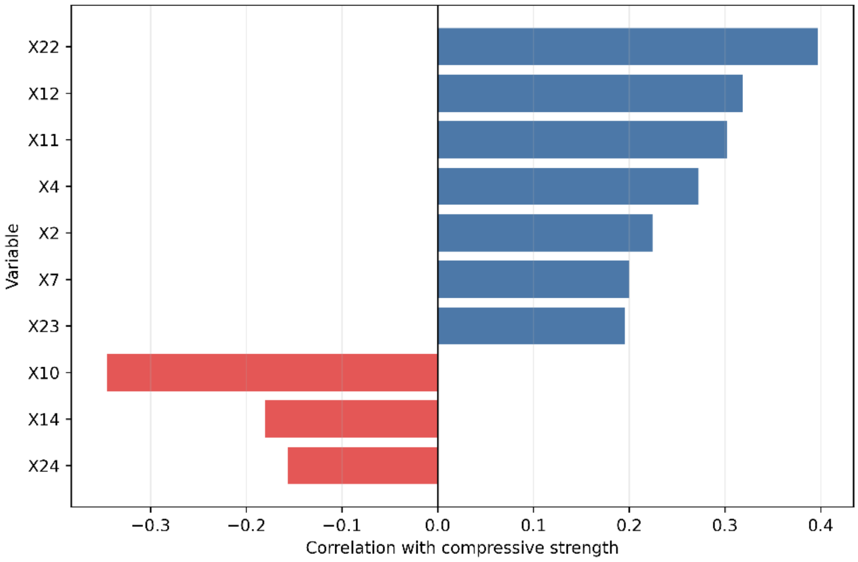

Figure 2. Correlation of input variables with compressive strength

Note: *The predictor variables were retained using their original dataset identifiers (X1–X24) throughout the analysis and visualization process. Based on the dataset documentation, X1 = Cement content, X2 = Cement compressive strength class, X3 = Cement type, X4 = Cement strength class, X5 = Fly ash content, X6 = Slag content, X7 = Silica fume content, X8 = Silica fume type, X9 = Quartz powder content, X10 = Sand content, X11 = Coarse aggregate content, X12 = Maximum aggregate size, X13 = Aggregate type, X14 = Water content, X15 = Superplasticizer content, X16 = Steel fiber length, X17 = Steel fiber diameter, X18 = Fiber aspect ratio, X19 = Steel fiber content, X20 = Specimen width, X21 = Specimen height, X22 = Curing time, X23 = Specimen diameter, and X24 = Specimen length. Compressive strength was used as the target variable.*

3.3 Predictive Performance of the Random Forest Model

To test the predictive ability of the Random Forest model, an independent test set from the same data was used, as well as five-fold cross-validation. The developed Random Forest model gave an R^2 of 0.9041 for the independent test dataset, as shown in Table 1. This model also achieved a high level of predictive accuracy with a mean absolute error (MAE) of 7.79 MPa and a root mean square error (RMSE) of 11.09 MPa. Apart from that, the R^2 value obtained by performing five-fold cross-validation was found to be 0.9178, which signifies the model performed well in various training-validation partitions.

Table 1. Random Forest model performance

Measure	**Value**
Test R^2	0.9041
Mean Absolute Error (MPa)	7.7871
Root Mean Square Error (MPa)	11.0931
Mean 5-Fold Cross-Validation R^2	0.9178
Standard Deviation of 5-Fold Cross-Validation R^2	0.0116

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As can be seen from Figure 3A, there is a good agreement between the experimental compressive strength value and the predicted value, with most of the values being very close to the ideal prediction line. There were no obvious systematic trends in the distribution of the residual errors shown in Figure 3B. The relatively even spread of residuals over the range of predictions suggests that the model was not overly biased toward either weaker or stronger mixtures.

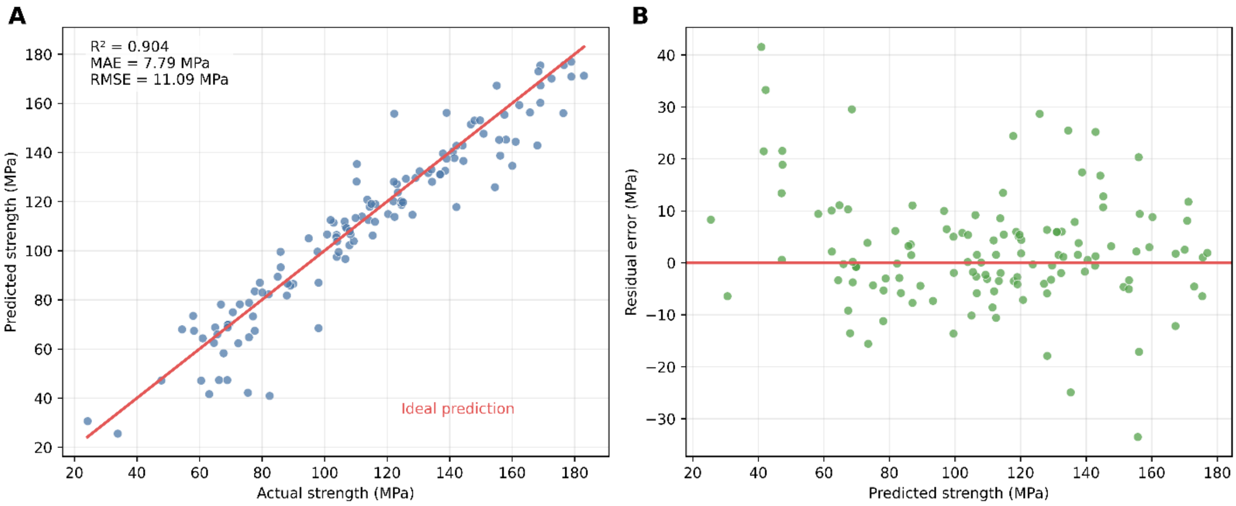

Figure 3. Random Forest predictive performance. (A) Actual versus predicted compressive strength. (B) Residual error distribution.

3.4 Importance of Input Variables in Strength Prediction

A quantitative estimation of the relative influence of each predictor variable was performed using Random Forest feature importance analysis. As presented in Table 2, the most influential variable was the curing time, which explained about 57.4% of the overall importance of the prediction. The curing time was the most significant predictor, whereas the other factors were not of such significance, underlining the crucial role of curing time on the development of the UHPC strength. Sand content (9.61%) is the second most important variable, followed by silica fume content (8.92%), cement content (5.29%), steel fiber content (3.69%) and superplasticizer content (3.66%). The maximum aggregate size and the coarse aggregate content showed relatively high positive linear correlation with compressive strength, but the values of feature importance were relatively low. The difference indicates that the Random Forest model was able to capture nonlinear relationships and interactions between the variables that were not adequately captured by pairwise correlations.

Table 2. Feature importance and correlation with compressive strength

Rank	Variable	Feature Importance	Correlation with Compressive Strength
1	Curing time	0.5736	0.3970
2	Sand content	0.0961	-0.3455
3	Silica fume content	0.0892	0.2002
4	Cement content	0.0529	0.0860
5	Steel fiber content	0.0369	-0.0971
6	Superplasticizer content	0.0366	-0.1143
7	Water content	0.0172	-0.1804
8	Coarse aggregate content	0.0152	0.3020
9	Maximum aggregate size	0.0136	0.3188
10	Slag content	0.0102	0.1264

A plot of curing time (time) alone is shown in Figure 4, and it is apparent that this variable dominates the other predictors. The curing time is significant in comparison with other variables, as shown by the high difference between the importance score of curing time and other variables. The other variables, on the other hand, are added together in more complex ways that are related to the composition of the mixture, the properties of the aggregates, and the reinforcement of the fiber.

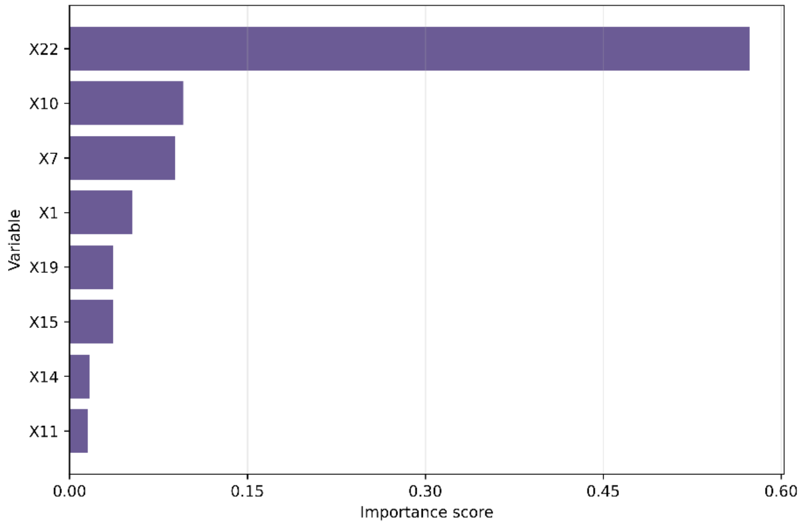

Figure 4. Relative importance of input variables in the Random Forest model

3.5 Marginal Effects of the Dominant Predictor Variables

Partial dependence analysis was performed to investigate the contributions of the two most influential parameters on the predicted compressive strength by averaging the effects of the rest of the parameters. As seen in Figure 5A, the higher the curing time, the greater the compressive strength. The compressive strength increased significantly as the curing time increased, especially at the early curing periods. The strength gain rate slowed down after about 150-200 days, suggesting a tendency towards stabilization at longer curing durations. As the amount of sand in the mix increased, there was a corresponding trend of decreasing predicted compressive strength, as indicated in Figure 5B. The negative correlation was not significantly different within the range observed with the proportions of sand used, which indicated that there might be a possible limitation in strength development due to excess proportions of sand in the cementitious matrix.

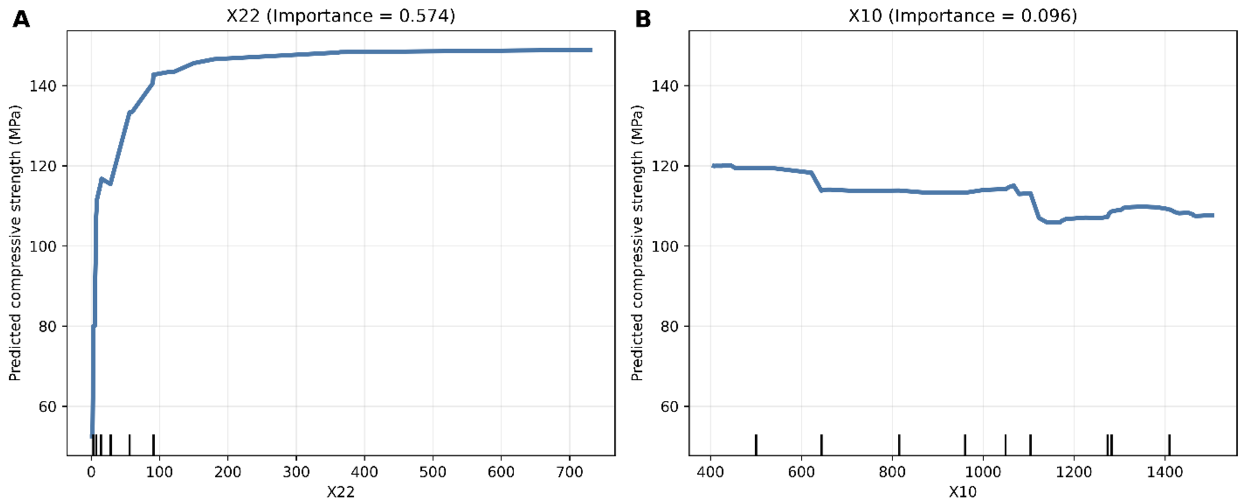

Figure 5. Partial dependence of the two most influential predictor variables. (A) Effect of curing time on predicted compressive strength. (B) Effect of sand content on predicted compressive strength

4. Discussion

The model of Random Forest showed good predictive ability for estimating compressive strength of UHPC, with an R^2 value of 0.9041 in the test and an average of 0.9178 in the five-fold cross-validation. The high consistency between the test and cross-validation results suggests that the model was not just reflecting the variation within a certain data split, but that a consistent relationship between the mixture-design variables and compressive strength was identified. Additionally, the relatively low MAE and RMSE values demonstrate that the model was able to obtain acceptable prediction errors in the wide compressive-strength range covered in the data. The most important feature was curing time, accounting for around 57.4% of the total feature importance. This is a reasonable result as the strength development of UHPC is closely related to the ongoing hydration, pozzolanic reaction and densification of the matrix with time. The partial dependence result also indicated that the predicted compressive strength increased sharply at the early curing time, then rose slowly at later curing times. This pattern suggests that the curing time has a nonlinear relationship; that is, higher increases in strength gain in the early and intermediate curing periods, and increasingly small strength gain in the later periods. The second most important variable was sand content, which was negatively correlated with the compressive strength. This indicates that this may have a negative impact on the relative effectiveness of the cementitious matrix, especially if the binder system and particle packing have not been proportionally optimized. In addition to curing time, silica fume content, cement content, steel fiber content, and the content of the superplasticizer made a contribution to the model, but with a lower importance than the curing time. In the difference between the correlation results and feature importance, it is found that there are other factors that are not linear, but they are affecting the compressive strength as well. Rather, the effects of curing duration, binder composition, aggregate properties and admixture content are multiplicative in affecting UHPC strength development.

The significant effect of curing time confirms previous experimental research, which has demonstrated that curing conditions can significantly affect the hydration, microstructure and mechanical properties of UHPC. Zuo et al. (2022) indicated that curing regime influences the strength development by influencing the changes in hydration products and pore structure, and Mohaisen et al. (2023) illustrated that the strength development of UHPC can be significantly impacted by the various curing methods. The present finding matches these studies as curing time was found to be the most influential variable, and it gave a positive, strong marginal effect on the predicted compressive strength. Because the Random Forest model has a high predictive accuracy, which is similar to recent machine-learning applications in the field of UHPC studies. Sun et al. (2023) showed that machine-learning models can be developed to predict comprehensive properties of UHPC and help in mixture design optimization. Similarly, Katlav and Ergen (2024) demonstrated the ability of machine learning models to predict the structural capacity of hybrid structures with UHPC composite materials. Based on the current results, it is concluded that data-driven modeling is also able to capture complex relationships in UHPC-related materials and structural applications.

In recent years, the role of machine learning in modelling specific mechanical responses of UHPC has also been highlighted. Mahmoodzadeh et al. (2025) used machine learning to predict the crack mouth opening displacement (CMOD) of UHPC, and Huang et al. (2026) created a strength prediction framework for fiber-reinforced UHPC with feature engineering and uncertainty quantification. In the present work, these studies have been complemented by a focus on compressive strength and a combination of predictive modeling with an interpretable analysis of dominant mixture design variables. The results of feature importance and partial dependence are in line with the trend of more emphasis on feature sensitivity and interpretability in the context of UHPC modeling. Zhou et al. (2025) pointed out that the sensitivity and uncertainty analysis, which can be used to predict the mechanical properties of UHPC, are of great importance. In line with this, Li et al. (2024) applied data-driven approaches to explore autogenous shrinkage behavior, demonstrating the potential of machine learning beyond prediction to understanding the material behavior. The present study is valuable in this regard because it indicates that the variables such as curing time, sand content and silica fume content are the variables that affect compressive strength prediction. The results are also in line with the recent advancement of modeling the compressive strength and analysis of sustainability with UHPC. Advanced machine-learning models were tested for the UHPC compressive strength by Tabani and Biswas (2025), and strength prediction was correlated with sustainability analysis by Rong et al. (2025). The strength prediction accuracy and interpretability provided by the present results are important for more efficient mixture design of UHPC.

The results have applications for the mixture design and performance evaluation of UHPC. The identification of curing time as the most important parameter confirms the need for controlling the curing time and conditions when aiming for high compressive strength. The observed effects of the quantities of sand and silica fume content also indicates that the proportioning of the aggregates and the refinement of the binders should be carefully selected, to ensure that the efficiency of the matrix is not lost. The modelling framework can also be used for some initial mixture screening prior to laboratory testing. Rather than experimenting in a trial-and-error fashion, engineering personnel can use data-driven prediction to limit the number of mixture designs to try. Feature importance and partial dependence analysis are useful in offering more insight about which variables to pay more attention to in the optimization process.

Some restrictions are noted. As this was a secondary study, it was not possible to control any variance in source materials, specimen preparation and testing conditions. Other UHPC properties (tensile strength, flexural strength, shrinkage, durability, and sustainability indicators) have not been analysed. The model was also only trained on Random Forest regression, and other algorithms could yield varying performance or rank. Further studies should be conducted with several UHPC properties, as well as other machine-learning models and similar preprocessing and validation procedures. In addition, further studies should include uncertainty analysis and optimization techniques to aid with the practical mixture design under performance, cost and sustainability requirements.

5. Conclusion

A data-driven framework was built to investigate the factors affecting the compressive strength of UHPC, where 626 observations were cleaned to remove outliers, and 24 variables related to the UHPC mixture design were examined. The predictive results of the Random Forest model were found to be good, with a test R^2 of 0.9041 and a mean 5-fold cross-validation R^2 of 0.9178, thus demonstrating its capability to detect the complex relationship between the UHPC mixture properties and compressive strength. The curing time was found to be the most dominant predictor with 57.4% of total feature importance. Partial dependence analysis also revealed that compressive strength grew rapidly in the initial curing period and then slowly levelled off at later curing times. The sand content had the greatest negative impact, and the silica fume content, cement content, steel fiber content, and superplasticizer content also had an influence on the strength prediction. The results show that interpretable machine learning can accurately predict strength, and also give some insight as to the variables that influence the performance of UHPC. This approach may help in preliminary mixture screening and to better design experiments to develop UHPC. The model should be expanded to other properties such as flexural strength, shrinkage, durability and sustainability indicators in future work.

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