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Research Article

Interpretable machine learning-based sustainability and sensitivity evolution analysis of ceramic waste concrete

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Abstract

The usage of natural resources has been largely increased due to construction activities and conventional concrete causes harmful effects to the environment. To reduce these impacts, shifting to sustainable construction materials in concrete technology is essential. Utilization of construction demolition wastes like ceramic tiles and ceramic powder is a better strategy to reduce solid waste footprint. In this study, waste ceramics and ceramic powder are used to partially replace coarse aggregates (0-100%) and cement (0-35%) respectively. Experimental evaluation of workability and mechanical properties was conducted for M20 grade concrete, followed by interpretable machine learning model to analyze the influence of different parameters. Sustainability–Performance Index (SPI) was calculated to integrate mechanical performance with environmental impacts, by quantifying the proposed concrete's carbon emission. Results indicate that while 28-day compressive strength shows less reduction by approximately 2.5% at 35% cement replacement, embodied CO_2 emissions reduction was achieved by nearly 32%. This indicates a maximum SPI improvement of about 44% compared to conventional concrete. The comparison of different ML models and parameters analysis by SHapley Additive exPlanations (SHAP) showed that cement related parameters influence strength development greatly, whereas aggregate replacement showed comparatively minor influence. Additionally, feasible ranges of ceramic waste utilization that maintain acceptable mechanical performance were identified using scenario-based predictions. The findings demonstrate that substantial carbon reduction can be achieved without compromising structural requirements, providing a robust decision-support framework for resilient infrastructure.

1. Introduction

Rapid urbanization, increase in population, and the ongoing need for infrastructure development have all contributed to increased expansion of global construction sector in recent decades. The quantity of solid waste produced has increased along with the growth of construction activities, making debris from construction and demolition sites one of the largest waste streams worldwide. Building methods now require materials that provide increased strength, durability, and cost effectiveness. Consequently, buildings that previously met standards are nowadays considered functionally obsolete. This rising trend of solid waste generation caused by the demolition of older buildings is now more common due to modernization requirements [1]. Despite being advantageous for urban development, this cycle of demolition and reconstruction puts tremendous strain on waste management systems.

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Ceramic tiles are commonly used all over the world especially in construction sector, with their usage growing daily [2]. In majority of buildings, certain ceramic products, such as tiles and sanitary ware, are now necessary building materials. These materials are discarded as solid waste once their useful lives are over, resulting in environmental drawbacks with problems in disposal. Ceramic waste is particularly problematic due to its high durability and non-biodegradable nature, which considerably slows down the natural degradation process and causes long-term accumulation in landfills. The production, transportation, and finishing processes of ceramic tiles, sanitary ware, and porcelain goods frequently result in high waste percentage. Also, manufacturing units that produce tons of ceramic materials leave about 15-30% of the ceramic production as waste [3], due to defects, breakage, or non-conformity with quality standards. This translates into large waste of millions of tones globally in single year. Also, as the ceramic waste has good strength, it can be recycled, used for aggregates, and other raw materials of concrete [2].

The other critical challenge faced by construction industry is the excessive utilization of natural resources, particularly natural aggregates extracted from rivers, mountains, and from quarries. The constant extraction of these natural resources carries severe environmental risks. These include depletion of riverbeds, loss of ecological balance, disturbance of landscapes, and soil erosion. Also, cement takes up approximately 50–70 % of the energy consumed while producing concrete [4]. Globally, almost 8% of CO2 emitted roots to cement industry, primarily as a result of the high-temperature kiln processes and limestone calcination. Numerous studies have demonstrated that different materials can effectively replace cement, coarse aggregate, and fine aggregate in the manufacturing environmentally friendly concrete. Materials with promising potential for supporting sustainable construction include fly ash, ground granulated blast furnace slag, granite powder, silica fume, ceramic powder, and recycled aggregates [5]. According to earlier studies, ceramic aggregate can also be potentially utilized as concrete's coarse aggregate [6] . Several experimental studies have reported that partial replacement of natural coarse aggregate with ceramic waste in the range of approximately 15–30% generally provides satisfactory mechanical performance while maintaining acceptable workability and durability characteristics. Beyond this range, the reduction in strength is often attributed to weaker interfacial bonding and the increased brittleness of ceramic aggregates [7]. In addition, because of the usage of tile-based aggregate, the self-weight of the concrete is reduced by approximately 4%, which helps make the structure economic [8]. Thus, the utilization of ceramic waste in concrete contributes to sustainable construction by reducing landfill disposal, conserving natural aggregates, lowering the consumption of virgin raw materials, and minimizing the environmental burden associated with conventional concrete production.

The incorporation of ceramic waste also promotes resource efficiency and has the potential to reduce production costs and embodied energy through partial replacement of cement and natural aggregates [9]. Furthermore, this research supports the objectives of Sustainable Development Goal (SDG) 11 (Sustainable Cities and Communities) and SDG 12 (Responsible Consumption and Production) by encouraging resource-efficient utilization of ceramic waste in concrete. Similar relationships between ceramic waste recycling and sustainable construction have also been highlighted in recent peer-reviewed studies [10,11]. The abundance of ceramic waste and the pozzolanic behavior of finely ground ceramic powder enable its use as a supplementary cementitious material. The amorphous silica and alumina phases present in ceramic powder contribute to secondary hydration reactions, resulting in improved microstructure, strength development, and enhanced long-term performance of concrete when used at appropriate replacement levels [12,13]. Particularly when the waste products are of different chemical composition, particle size, etc., this will bring the additional variability. Traditional experimental procedures alone can't easily provide a detailed understanding about interactions between mix parameters, curing and mechanical performance. It would require a lot of laboratory experiments to do all combination of replacement level, water to cement ratio, proportion of aggregates, and age of curing. This will be also expensive, time and labor consuming. These restrictions have promoted the adoption of sophisticated computational methods, such as ML, to learn and forecast the concrete properties. ML algorithms can identify patterns in datasets and learn relations among the inputs and outputs [14,15].

Recent studies have increasingly studied about the utilization of ceramic waste in sustainable concrete production aiming for reducing the impact in landfill. Many such works have reported that partial replacement of natural aggregates with ceramic waste can perform similar to conventional concrete at low replacement levels. However, high substitution negatively impacts the strength due to weaker interfacial transition zones and increased brittleness. Similarly, ceramic powder has found to have pozzolanic activity capable which can be utilized for cement reduction while lowering embodied carbon emissions [6,16]. Also, machine learning techniques have been used now-a-days for various applications [17] including predicting concrete properties involving waste-derived materials. Ensemble-based approaches such as Random Forest, Gradient Boosting, and XGBoost have showed high prediction capability compared to linear regression models. Explainable artificial intelligence approaches, especially SHAP analysis, have further used by studies to interpret feature importance and parameter sensitivity in concrete studies [18,19]. However, previous studies mostly focused either on mechanical characterization or strength prediction independently. Limited studies have integrated experimental validation, interpretable machine learning, and embodied carbon-based optimization for ceramic waste concrete.

A systematic investigation was conducted in the current study to determine the outcome of replacing coarse aggregate with ceramic and tile-based aggregate, and cement with ceramic powder. The replacement percentage were changed to see how it affected the properties of M20 grade concrete including strength and workability. Additionally, the study compared and analyzed the predictive power of different models based on experimental data using machine learning. The models were selected to provide a comparative balance between ensemble-based, nonlinear, and linear machine learning techniques [18,20,21]. To assess the impact of all the parameters individually in the ceramic waste-based concrete's strength, SHAP analysis was carried out. By encouraging the utilization of waste ceramic pieces and powder in concrete, this research helps lessen the adverse negative impact to environment generated through traditional concrete manufacturing. The results of this study align with SDGs 9 (Industry, Innovation, and Infrastructure), 11 (Sustainable Cities and Communities), 12 (Responsible Consumption and Production), and 13 (Climate Action) through the reduction of cement-related CO_2 emissions and enhanced resource efficiency in construction practices.

While previous studies have largely focused on evaluating the mechanical performance or developing predictive models for ceramic waste concrete, limited attention has been given to integrating environmental impact quantification with structurally constrained performance assessment. Moreover, the combined influence of ceramic coarse aggregate replacement and ceramic powder substitution on strength development has not been systematically examined. [22–25]. Despite the significant progress in machine learning applications for concrete property prediction, relatively few studies have developed interpretable decision-support frameworks that simultaneously integrate experimental validation, sustainability assessment, and optimization of ceramic waste concrete mixtures. Consequently, the development of practical machine-learning-based decision-support tools for identifying feasible and sustainable replacement combinations remains an important research gap [3,26]. SPI is calculated under structural strength constraints to enable eco-efficient mix selection. The objectives of this work were:

- To experimentally investigate the effects of crushed ceramic waste as partial replacement of natural coarse aggregates and ceramic powder as partial cement substitute on the workability and mechanical properties of M20 grade concrete.
- To develop and evaluate machine learning models including Multiple Linear Regression, Decision Tree Regression, Random Forest, and Support Vector Regression for predicting compressive, split tensile, and flexural strengths.
- To apply explainable machine learning using SHAP to quantify the influence of material parameters and curing age on strength development.
- To conduct scenario-based predictions under structural constraints to identify feasible and eco-efficient replacement combinations.

2. Materials and Methods

The methodology adopted in this study consists of three main components: (i) experimental investigation of concrete using ceramic waste as partial replacement of coarse aggregates and cement, (ii) development of machine learning models to predict the mechanical properties of the modified concrete and (iii) to apply SHAP model and the calculation of SPI. The experimental phase provided a reliable dataset for training and evaluating the machine learning models, while the modelling phase enabled data-driven interpretation and scenario-based prediction. The flowchart describing the methodology is shown in Figure 1.

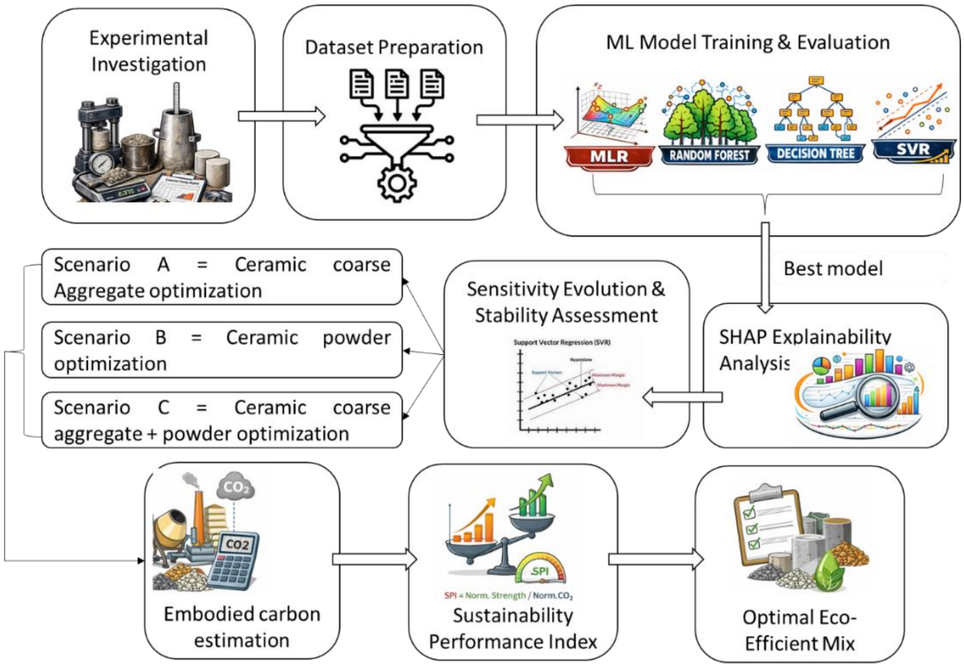


Fig. 1. Methodology flow chart

2.1. Experimental Evaluation of Ceramic Based Concrete

The first phase of this study makes experimental samples to evaluate the fresh and hardened properties of concrete incorporating ceramic waste as partial replacement of natural coarse aggregates and cement. Grade 43 cement of Ordinary Portland Cement with the brand name Sankar Cement was bought from the local market nearby. The suitability of this cement for the study was investigated through the consistency, setting time (initial and final), compressive strength, and the results satisfied IS 4031 (Part IV) code limits [27]. The results of this test are shown in Table 1.

Table 1. Properties of cement

Sl. No	Properties of cement		
	Properties	Test results	IS: 4321 (Part IV)
1.	Consistency	0.30%	
2.	Initial setting time	30 min	Minimum of 30 min
3.	Final setting time	310 min	Maximum of 600 min
4.	Compressive strength:		
	3days strength	24.2 MPa	Minimum of 23 MPa
	7days strength	34.6 MPa	Minimum of 33 MPa
	28days strength	46.6 MPa	Minimum of 43 MPa

The fine aggregate used in this study was river sand bought from the nearby construction site and tested for its moisture content and specific gravity. From sieve analysis, it was founded that the sand belonged to zone III. Similarly, the coarse aggregate of average size 20 mm, bought from a nearby crusher, was checked for its specific gravity, fineness modulus and water absorption. The fine and coarse aggregate tests are shown in Table 2 and 3, respectively, which satisfied IS 383-

1970 [28]. The ceramic pieces used for the study were collected from electric waste dumping sites as ceramics were used in transformers and from tiles shops, where broken tiles were collected.

Table 2. Properties of fine aggregate

S. No	Description Test	Result
1	Sand zone	Zone- III
2	Specific gravity	2.591
3	Free Moisture	0.9%

Table 3. Properties of coarse aggregate

S. No	Description	Ceramic waste aggregate	Natural Aggregate
1	Origin Rock	Feldspar	Basalt
2	Specific gravity	2.63	2.69
3	Water absorption	0.19%	0.15%
4	Crushing strength	26.5%	24.8%
5	Impact strength	28.7%	25.2%

The waste ceramic pieces were broken into small pieces and the required size, which is an average of 20mm, is separated for this study. Using various sizes of sieves, the suitable size (20 mm to 12 mm) is separated and used as partial substitution for natural coarse aggregate. The ceramic aggregates, which are less than 4.75 mm in size, were neglected as per previous studies [1]. Previous studies have shown that coarse aggregate partially replaced with 25% optimum of tile aggregate is satisfactory, and the ceramic waste aggregate concrete showed similar concrete properties like the conventional concrete [16,29]. Another study shows that replacement of waste tile aggregate should be 5-30% because after 30% replacement, the strength decreases [23,30].

The ceramic waste powder was collected from a nearby tile company at low cost. For analyzing the suitability of the crushed ceramic waste and ceramic powder in the concrete mix, tests are done separately for the cement, fine, coarse aggregate, ceramic aggregate and ceramic powder to check their specific gravity, water absorption, fineness modulus, consistency. M20 grade concrete was designed in accordance with IS 10262:2019 [31], and a conventional mix without ceramic replacement was prepared as the control. A total of nine mixes are prepared along with the conventional mix (M0). The coarse aggregates are partially replaced by 25%, 50%, 75% and 100% of crushed ceramic aggregate and the cement is replaced by 10%, 20%, 30%, and 35% of ceramic powder individually. The details of mix codes corresponding to various replacements of coarse aggregate and cement are given in Table 4. The workability of the fresh concrete is obtained using the Slump cone test. Figure 2 shows the ceramic concrete and sample of experimental works.

Table 4. Details of aggregate and cement replacement for mix codes

Sl.No	Mix code	Fine aggregate (sand) (%)	Coarse aggregate (%)		Cement (%)	
			Natural Coarse Aggregate	Crushed tiles	OPC of 43 grades	Ceramic Powder
1	M0	100	100	0	100	0
2	M1	100	75	25	100	0
3	M2	100	50	50	100	0
4	M3	100	25	75	100	0
5	M4	100	0	100	100	0
6	M5	100	100	0	90	10
7	M6	100	100	0	80	20
8	M7	100	100	0	70	30
9	M8	100	100	0	65	35

After casting, to prevent moisture loss in the concrete specimens, they were covered and then demolded after 24 hours. All specimens were subsequently immersed in clean water maintained at a temperature of 27 ± 2°C, in accordance with IS 516 [32]. Mechanical testing was conducted at curing ages of 7, 14, and 28 days to capture early-age and later-age strength development. Compressive strength tests were performed using a calibrated compression testing machine following IS 516 [32]. The compressive strength was calculated using the equation (1)

$$f_c = \frac{P}{A} \tag{1}$$

where fc is the compressive strength in MPa, P represents the maximum load applied at failure in Newtons, and A denotes the cross-sectional area of the concrete cube in square millimeters.

Fig. 2. Experimental works on ceramic concrete

2.2. Development of Machine Learning Models

The machine learning analysis was conducted on the dataset developed from the experimental results with 81 data points from nine concrete mixtures tested. The input variables consisted of age of curing, percentage of coarse aggregate and cement replacement with ceramic waste. Compressive strength, split tensile strength, and flexural strength were the output variables. Although the dataset size is moderate, repeated cross-validation, constrained model complexity, and explainable ML techniques were adopted to improve robustness and avoid overfitting. Before development of the model, the dataset was statistically analysed in order to determine consistency and to spot possible anomalies. Algorithms were however normalised where it was needed. One of the most commonly used baseline methods of prediction is the Multiple Linear Regression (MLR). MLR forms a linear correlation between input variables and output responses, which is helpful in determining overall trends between curing, mechanical strength, material replacement levels, and age [33]. In research which are done on partial replacement of cement or aggregates, MLR has been widely used in assessing the direct effect of industrial or ceramic waste percentage of replacement on decrease or improvement in strength 19]. Variance Inflation Factor (VIF) analysis was conducted before MLR modelling, and all predictor variables exhibited VIF values below 5.

Table 5. Variance Inflation Factor (VIF) values of predictor variables

S. No	Predictor Variable	Result
1	Curing Age	2.42
2	Ceramic Aggregate Replacement	2.68
3	Ceramic Powder Replacement	2.81

Decision Tree Regression (DTR) is a non-parametric machine learning that has the ability to model nonlinear relationships in a recursive partitioning of the input feature space. Unlike linear models, DTR need not have predefined functional relationships and is naturally able to represent threshold-based behaviour which is generally found within the concrete mixtures. However, there is the tendency of single decision trees to overfit, particularly to small experimental samples. Despite this limitation, DTR has its merits in comprehending rule-based interactions between variables and is the basics to higher-level ensemble methods [19,34]. RF is an ensemble learning technique that builds several decisions trees and combines their results, thus decreasing the extent of overfitting and enhancing the accuracy. Its ability to handle high- dimensional datasets and measure the feature importance, makes it appropriate to analyse mixtures that use material such as ceramic waste [20]. RF is also an attractive predictive tool because it can make strong predictions with a comparatively sizable dataset [35]. Support Vector Regression (SVR) was added as an additional modelling method because of its strong performance in the possibility to deal with nonlinear relationships in small to medium-sized datasets. The radial basis function (RBF) was used with the SVR model kernel to determine the nonlinear correlations between curing age, ceramic aggregate replacement, ceramic cement replacement, and mechanical properties developed. Due to its capability easy interpolation, SVR was especially appropriate to prediction of scenarios in this work [34,36].

The machine learning models chosen underwent hyperparameter tuning to obtain balanced predictive performance without overfitting. In the case of the Random Forest model, important parameters like number of trees and the maximum tree depth were tuning through trial-based tuned based on cross-validation performance. Tuning of the Decision Tree model was tuned by regulating tree depth and maximum number of split samples to minimize the model complexity [37]. In the case of the SVR model, the generalisation is improved by tuning the penalty parameter (C), epsilon margin, and kernel coefficient (gamma). Given the moderate size of data, optimisation methods that are computationally intensive were not employed and model simplicity was also given importance to achieve robustness and reproducibility [38]. The dataset was divided into training and testing subsets using an 80:20 split ratio. Stratified sampling was not used for dataset partitioning as this is a regression modelling study. Instead, a random train–test splitting and repeated k-fold cross-validation were used in order to guarantee a representative distribution of curing ages and replacement levels and to keep consistency with the methodological approach of standard regression modelling.

The standard regression measures such as the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) were used to assess model performance. These metrics facilitated objective evaluation of predictive power and generalization potential of the models [39]. SHAP (SHapley Additive exPlanations) is an explainable artificial intelligence (XAI) technique based on cooperative game theory that quantifies the contribution of each input variable to the prediction generated by a machine learning model. By assigning Shapley values to individual features, SHAP provides both global and local model interpretability, enabling transparent assessment of feature importance and prediction behavior. Owing to these advantages, SHAP has been increasingly adopted for interpreting machine learning models in civil engineering and sustainable concrete research [40,41]. The algorithm TreeExplainer was applied on the trained Random Forest model to calculate SHAP values in an efficient manner. Both global SHAP summary plots and feature dependence plots were generated. To control overfitting, repeated k-fold cross-validation was employed, and model complexity was regulated through hyperparameter tuning such as limiting tree depth and adjusting regularization parameters [42]. In addition to predictive modelling, scenario-based optimisation was conducted to identify feasible replacement combinations satisfying structural performance requirements while improving environmental efficiency. Three optimisation scenarios were considered:

- Variation of ceramic coarse aggregate replacement (0–100%) with cement replacement fixed.
- Variation of ceramic powder replacement (0–35%) with aggregate replacement fixed.
- Simultaneous variation of both replacement parameters within experimental limits.

For each scenario, predicted 28-day compressive strength values were generated. Feasible combinations were filtered based on the structural requirement of minimum 20 MPa compressive strength in accordance with IS 456:2000 for M20 grade concrete.

2.3. Sustainability–Performance Index

To quantitatively evaluate the advantages of ceramic waste incorporation in concrete carbon reduction, the embodied carbon of each concrete mix was estimated based on emission factors for each material used. The assessment was conducted per cubic meter of concrete for each mix proportions. The total embodied CO_2 emissions (kg/m^3) were computed as:

$$CO_2 = \sum (m_i \times EF_i) \quad (2)$$

where m_i represents the mass of each constituent material (kg/m^3) and EF_i denotes the corresponding emission factor (kg CO_2/kg). A value of 0.90 kg CO_2/kg was used as emission factor for OPC, consistent with global cement production emissions reported by IPCC [43–45]. Natural aggregates and sand were assigned 0.01 kg CO_2/kg based on extraction and processing data from ICE [43]. Since ceramic powder and crushed ceramic tiles are waste-derived materials, only processing-related emissions were considered, adopting conservative values of 0.02 kg CO_2/kg and 0.005 kg CO_2/kg respectively, as supported by lifecycle assessment studies of recycled ceramic materials [46–48]. Sustainability–Performance Index (SPI) was introduced to integrate the mechanical performance with environmental impact. The 28-day compressive strength of M20 grade concrete was used as the structural performance parameter. In accordance with IS 456:2000, a minimum strength threshold of 20 MPa at 28 days was considered acceptable for structural applications. For comparative evaluation, embodied carbon and compressive strength were normalized relative to the control mix (M0). An SPI value greater than unity indicates improved eco-efficiency relative to conventional concrete.

$$SPI = \frac{Normalized\ Strength}{Normalized\ CO_2} \quad (3)$$

where, $Normalized\ Strength = \frac{f_{c,mix}}{f_{c,control}}$ and $Normalized\ CO_2 = \frac{CO_{2,mix}}{CO_{2,control}}$

The Sustainability–Performance Index (SPI) was developed as a comparative indicator to evaluate the balance between mechanical performance and embodied carbon emissions among the investigated concrete mixtures. The SPI assessment was performed using a cradle-to-gate system boundary considering material production and processing stages only. Transportation, construction activities, maintenance, and end-of-life phases were not included in the present analysis. Therefore, SPI values should be interpreted as relative indicators for comparing alternative concrete mixtures under consistent assumptions rather than as comprehensive measures of overall sustainability.

3. Results and Discussion

3.1. Mechanical Performance of Ceramic Waste Concrete

After conducting the workability tests, cubes of size 150 x 150 x 150mm were cast and tested for 7 days, 14 days and 28 days, after. Split tensile strength values were obtained by testing the cylindrical specimen. The workability from the slump cone test increases as the mix proportion replacement increases. It increased by quantity of 3.17%, 7.93%, 15.87%, 23.81%, 1.59%, 1.59%, 4.76% and 6.35% for M1, M2, M3, M4, M5, M6, M7 and M8 mixes respectively over conventional M20 concrete grade (M0). Overall, the workability of the concrete lies in mid-range. The experimental results indicate a gradual reduction in compressive, split tensile, and flexural strengths with increasing levels of ceramic waste replacement at all curing ages. For compressive strength, the reduction ranged from marginal values (below 1%) at lower replacement levels to a maximum of approximately 3% at higher replacement combinations, with the effect being more pronounced at early curing ages and diminishing at 28 days. The mechanical properties of different mixes of concrete are shown in table 6 and figure 3.

Table 6. Concrete properties

Sl. No	Mix Designation	Workability (mm)	Compressive strength N/mm2			Split tensile strength N/mm2			Flexural tensile strength N/mm2		
			7 days	14 days	28 days	7 days	14 days	28 days	7 days	14 days	28 days
1	M0	63	18.16	20.35	27.40	1.90	2.53	3.40	2.470	2.730	3.620
2	M1	65	18.10	20.32	27.36	1.87	2.51	3.32	2.465	2.721	3.610
3	M2	68	18.07	20.30	27.31	1.85	2.47	3.30	2.457	2.717	3.590
4	M3	73	17.95	20.27	27.28	1.81	2.45	3.28	2.452	2.713	3.560
5	M4	78	17.80	20.25	27.17	1.78	2.42	3.25	2.436	2.705	3.520
6	M5	64	18.00	20.31	27.32	1.86	2.25	3.33	2.455	2.720	3.600
7	M6	62	17.91	20.28	27.27	1.83	2.48	3.31	2.430	2.715	3.570
8	M7	60	17.83	20.26	27.13	1.79	2.45	3.27	2.410	2.707	3.530
9	M8	59	17.60	20.23	26.73	1.75	2.42	3.23	2.403	2.700	3.490

Among all mixes, M1 (25% coarse aggregate replacement) exhibited the highest strength values, demonstrating that limited ceramic aggregate substitution can be effectively accommodated. This is consistent with earlier research that found that replacing 30% of the ceramic tile aggregate with natural coarse aggregate yields the highest compressive strength [23]. However, all the mixes achieved target strength agreeing with other studies which show that usage of ceramic waste in concrete gives the strength which is equivalent to ordinary concrete [22,24].

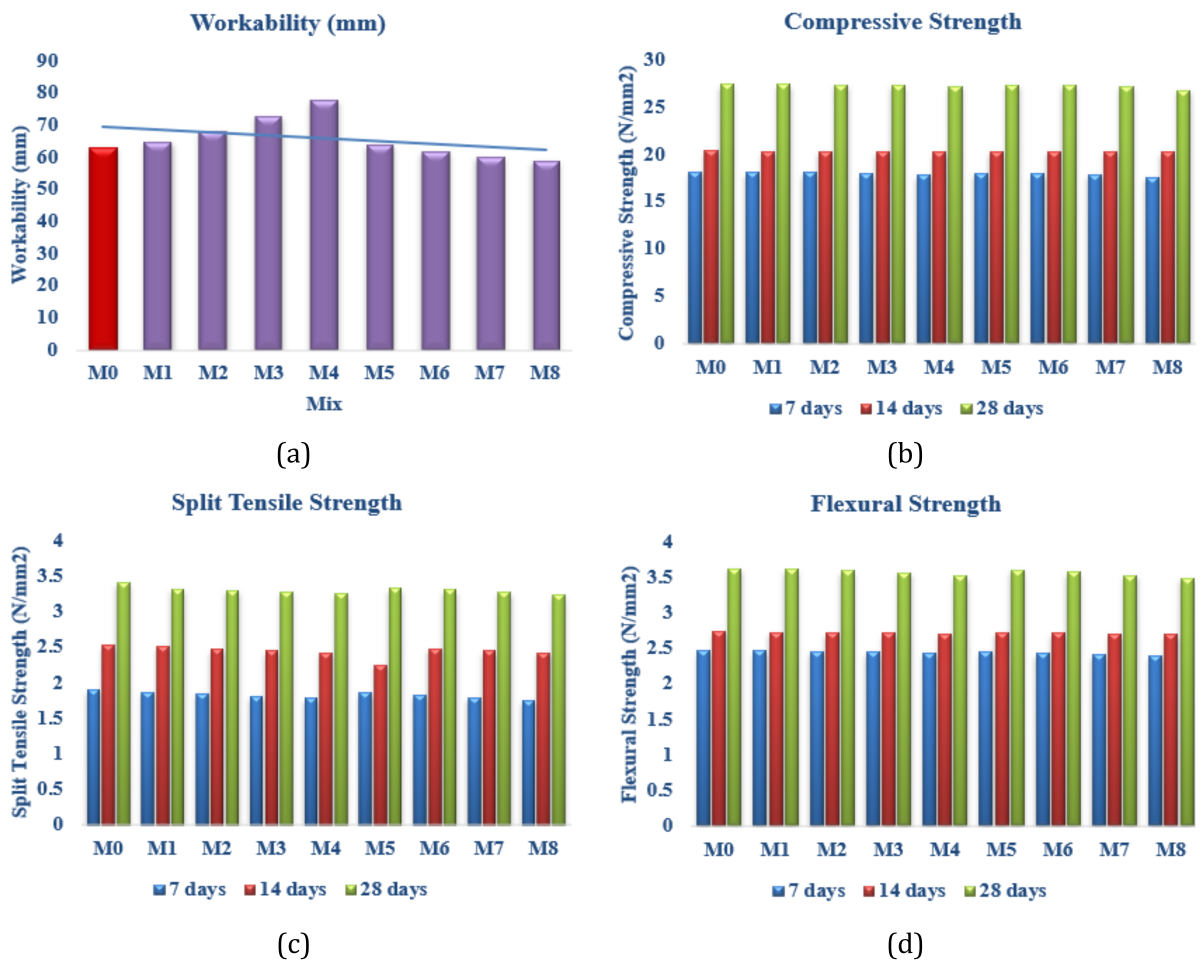


Fig. 3. (a) Workability (b) Compression strength (c) Split tension strength (d) Flexural strength

Split tensile and flexural strengths followed similar trends, with strength reductions increasing progressively with higher replacement levels. However, at lower ceramic contents, the losses remained minimal, indicating acceptable mechanical performance. Similar to previous studies, the inclusion of ceramic powder contributed to improved workability and showed a limited influence on strength reduction at moderate replacement levels [49]. The strength values show average results obtained from experimental specimens. Minor variability was observed across samples, however, the overall trends remained consistent, supporting the reliability of the experimental observations. Overall, the results confirm that ceramic waste can be incorporated into concrete in controlled proportions with only minor reductions in mechanical performance, particularly at later curing ages.

3.2. Machine Learning Model Performance

With an R^2 value of 0.806, an RMSE of 0.133 MPa, and an MAE of 0.085 MPa, the Random Forest model had the best predicted accuracy for compressive strength. This suggests that the experimental and anticipated values have a strong association. The good performance of the Random Forest model may be attributed to the existence of ensemble-based learning format which captures the nonlinear interactions between curing age, replacement of ceramic aggregate, and replacement of ceramic powder, and at the same time, with minimalization over fitting. The predictive ability of the Decision Tree Regression was also reasonable (R^2 = 0.769) but the value is greater in RMSE and MAE than that of RF implying less generalisation capacity. Multiple Linear Regression was not doing very well (R^2 = 0.649), proving that linear correlations only are inadequate in modelling the complicated behaviour of ceramic waste concrete. The lowest performance of regression was observed in compressive strength by Support Vector Regression (R^2 = 0.202), which suggests its limited appropriateness to this particular predictive exercise based on the current dataset. Similar studies using waste material-based concrete which used machine learning for predicting strength have also showed similar results, where ensemble and tree-based models consistently outperformed linear and kernel-based approaches [42,50,51]. The Taylor's diagram showing the performance of all the models is shown in figure 4.

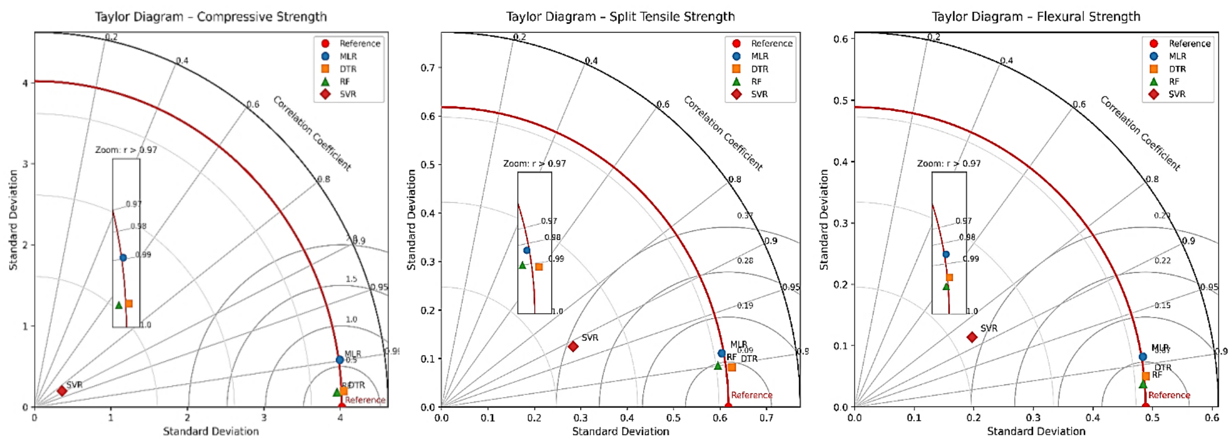


Fig. 4. Taylor Diagram compression, split tension and flexural strength

Regarding the split tensile strength, there was a relatively close proximity between all tree-based and linear models' performance. Decision Tree Regression was the one that had the highest R^2 (0.792) next was Multiple Linear regression (0.779) and Random Forest (0.771). However, the Random Forest generated the least RMSE (0.071 MPa), MAE (0.044 MPa), indicating better error control and more robust predictions even with a slightly reduced value of R^2. The relatively high results of MLR in split tensile strength prediction show that there is a more linear relationship between input parameters and tensile behaviour, especially at a low replacement level. Conversely, SVR obtained a negative value of R^2 (-0.140) which means that it does not predict well and that it cannot be generalised to the whole population, probably because it is highly sensitive to parameter tuning and size of dataset. In flexural strength prediction, the best model was Decision Tree Regression with an R^2 of 0.851, RMSE of 0.025 MPa, and MAE of 0.018 MPa. That was closely followed by Random Forest with an R^2 of 0.821 and similar error values. The strong performance of flexural strength tree-based models shows that, flexural behaviour is dictated by threshold-type interactions and material discontinuities, that are well represented by decision-based learning structures. Multiple Linear Regression once again showed moderate results (R^2 =0.709), but The Support Vector Regression had low predictive ability with a highly negative R^2 value (– 0.654), which implies that the model is unstable and cannot capture flexural behaviour at ceramic waste modification. In general, tree models, especially the Random Forest and Decision Tree Regression showed better predictive ability in all mechanical properties. Random Forest repeatedly yielded both balanced performance and low prediction errors and high generalisation, particularly with compressive strength, which is the most vital design factor in concrete usage. Although Decision Tree Regression slightly outperformed RF in flexural strength prediction, RF was selected as the primary predictive model due to its robustness, resistance to overfitting, and suitability for model interpretation using SHAP analysis. Support Vector Regression showed inconsistent performance across all strength parameters, with negative R^2 values for split tensile and flexural strength, indicating limited applicability for the present dataset. The relatively poor performance of SVR may be attributed to the limited dataset size and the narrow variability range of the experimental responses. This reduces the effectiveness of kernel-based learning methods. In contrast, tree-based models were better able to capture localized nonlinear relationships in the dataset. Therefore, SVR was not considered for primary model interpretation. However, even though it exhibited comparatively weaker predictive performance, it was retained for scenario-based interpolation due to its smooth nonlinear regression characteristics. The SVR-based predictions were restricted within the experimentally observed parameter range and were interpreted cautiously as exploratory trends rather than definitive outcomes.

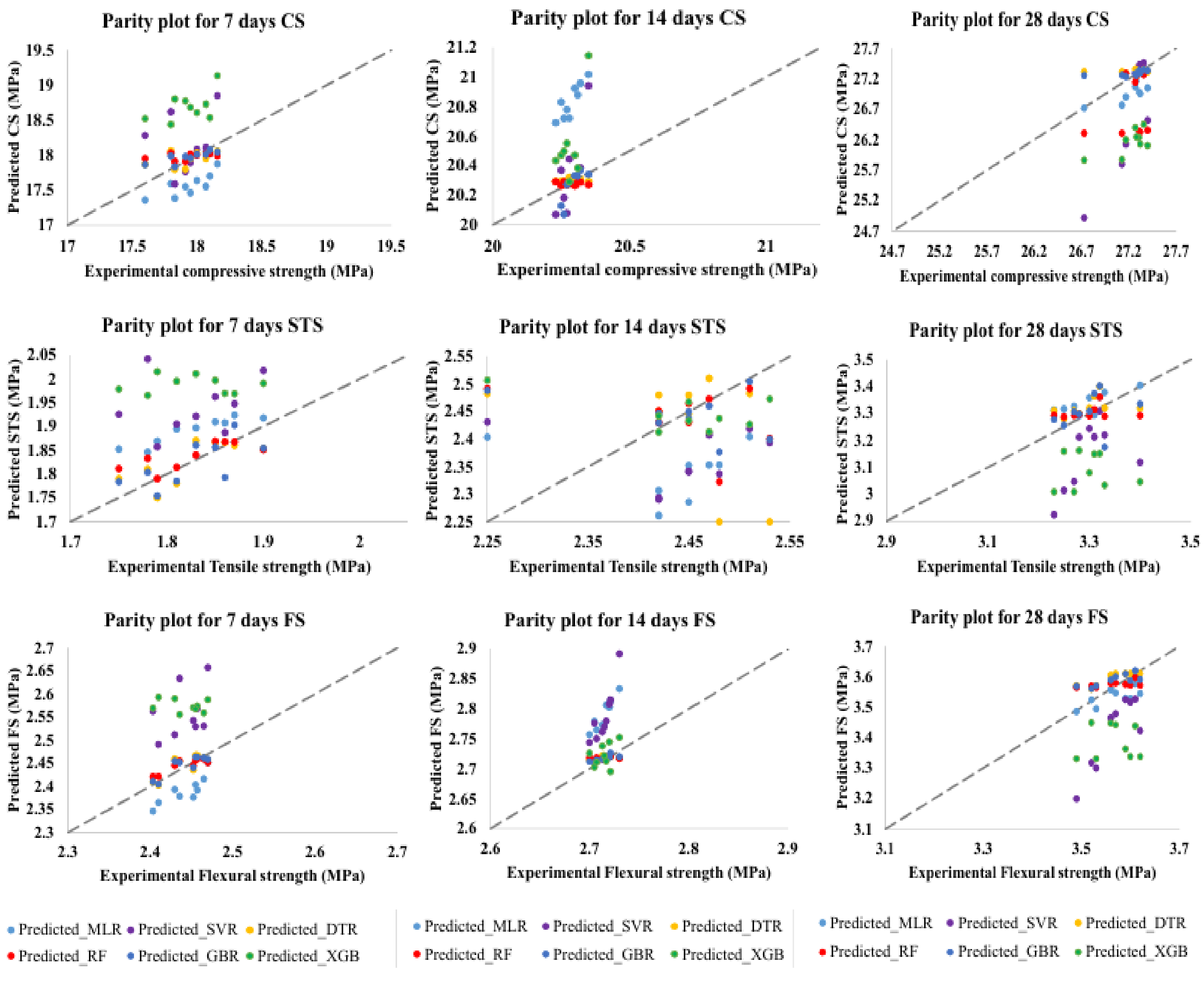


Fig. 5. Parity plots for concrete strength

The Taylor diagram confirms consistency between predicted and experimental values, indicating acceptable generalization despite the moderate dataset size. Parity plots for 7, 14, and 28 days in figure 5 demonstrate satisfactory agreement between predicted and experimental values across curing ages. For compressive strength, predictions at 28 days exhibit the closest clustering around the 45° reference line, indicating improved predictive stability at later curing stages. Greater dispersion is observed at 7 days, reflecting higher variability associated with early-age strength development. A similar trend is observed for split tensile and flexural strengths, where model predictions align more closely with experimental values at 28 days compared to early curing ages. The moderate scatter observed in tensile and flexural strength predictions may be attributed to the inherently higher sensitivity of these properties to microstructural variations. Overall, ensemble-based models (RF/GBR) show comparatively tighter clustering around the parity line, suggesting better generalization performance relative to linear and single-tree models. These results confirm that machine learning models are capable of capturing nonlinear interactions between curing age and ceramic waste replacement parameters, with prediction reliability improving as curing progresses.

3.3. Model Interpretation Using SHAP Analysis

To enhance the interpretability of the developed machine learning models and to understand the influence of ceramic waste parameters on concrete strength, SHapley Additive exPlanations (SHAP) were employed. SHAP analysis was performed on the Random Forest model for compressive strength prediction and on the Decision, Tree models for split tensile and flexural strength, aligning with the best-performing models for each mechanical property. To minimise the high influence of curing age and to isolate the material-specific effects of ceramic waste and ceramic powder, SHAP analysis was performed for 28 days strength. Since 28-day strength is the standard design criteria, this provides practically relevant interpretation. The SHAP summary plot for compressive strength in figure 6 shows that ceramic powder replacement (cement replacement) has a greater influence than ceramic coarse aggregate replacement. The distribution of SHAP values showed a wider spread for cement replacement, indicating higher sensitivity of compressive strength to variations in ceramic powder content. Increasing ceramic powder replacement beyond moderate levels resulted mostly in negative SHAP contributions, indicating reduction in compressive strength.

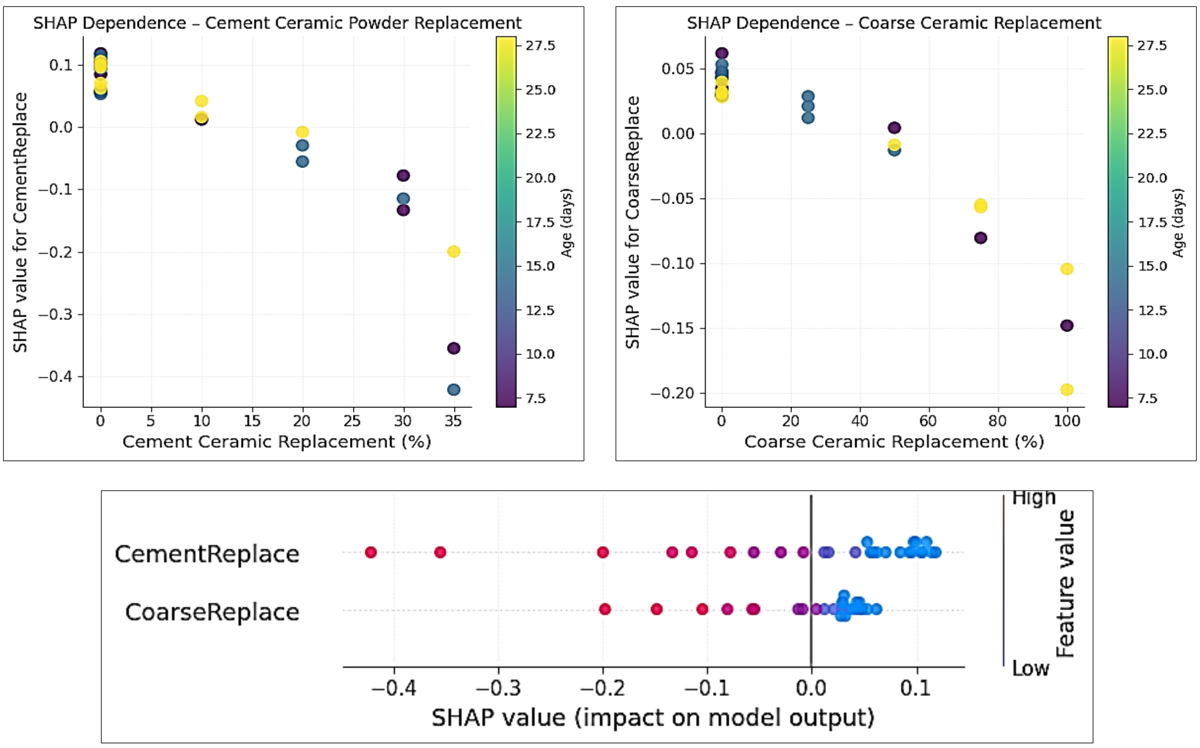


Fig. 6. SHAP for compression strength

A similar trend was observed for split tensile and flexural strengths which is shown in figures 7 and 8. In the case of split tensile strength, SHAP analysis on the Decision Tree model showed the same trends with the replacement of ceramic powder once more turns out to be the more significant parameter. The SHAP values showed that an increase in cement replacement levels invariably led to the decrease in tensile strength, which is manifested in how tensile behaviour is sensitive to both matrix continuity and paste quality. Ceramic coarse aggregate replacement had a moderate effect, and the SHAP was not only positive but also negative contributions seen at reduced replacement levels. This implies that a low amount of ceramic aggregate substitution can have a minimal negative impact on tensile strength, and maybe because of better mechanical interlocking due to angularity of the ceramic particles. At greater replacement percentages though, contributions that were negative took over, presumably because of smaller interfacial transition zones and larger brittleness.

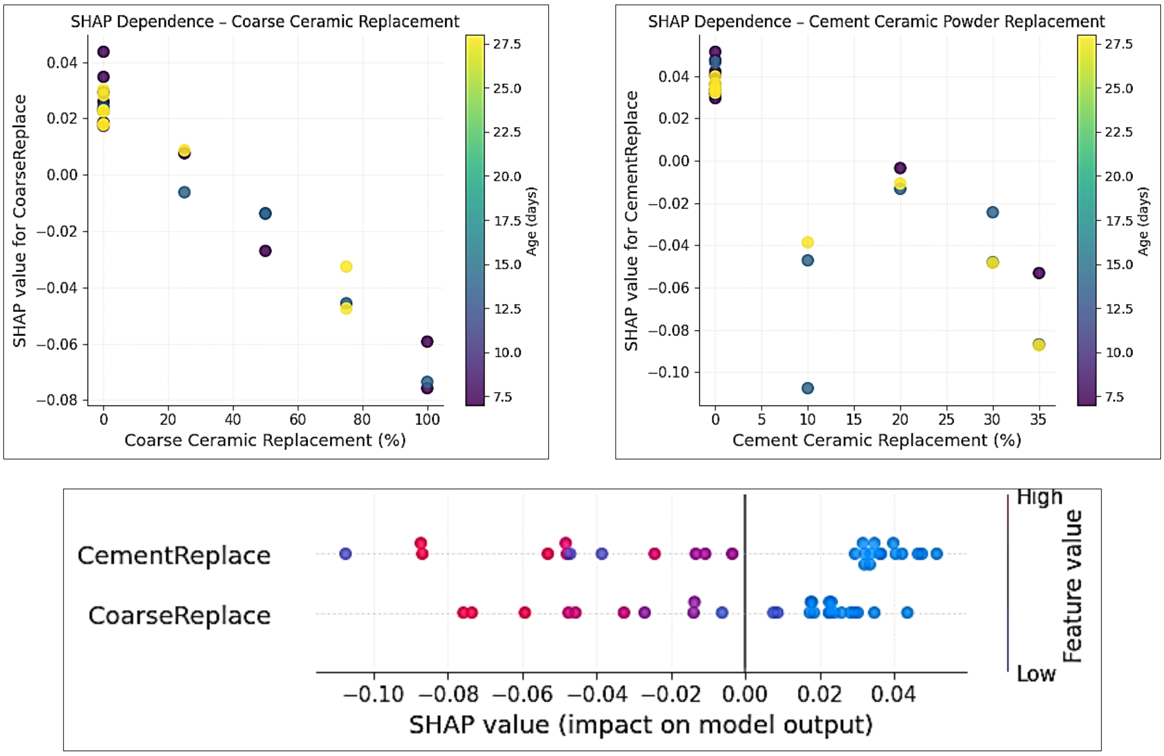


Fig. 7. SHAP for split tensile strength

SHAP summary plot of flexural strength also affirmed the sensitivity of ceramic powder replacement versus ceramic coarse aggregate replacement. Replacement of cement manifested the highest value of SHAP, which means that it has a significant effect on flexural performance. Elevated negative SHAP values were linked to levels of replacement of ceramic powder, indicating decreases in flexural strength as a result of a decrease in the stiffness of the paste and the ability to bridge a crack during bending.

Replacement with ceramics aggregates was not as effective in flexural strength changes, though at increased levels of replacement, negative effects were observed. The comparatively lower sensitivity of flexural strength to aggregate replacement suggests that flexural behaviour is governed more by paste quality and matrix integrity than by coarse aggregate substitution alone. Across all three mechanical properties, SHAP analysis consistently demonstrated that ceramic powder replacement is a more sensitive parameter than ceramic coarse aggregate replacement when curing age is fixed. This indicates that the cement substitution levels must be more carefully controlled than aggregate replacement to maintain mechanical performance. While ceramic aggregate can be utilised at moderate levels with limited strength penalties, excessive ceramic powder replacement leads to more pronounced reductions in compressive, tensile, and flexural strengths.

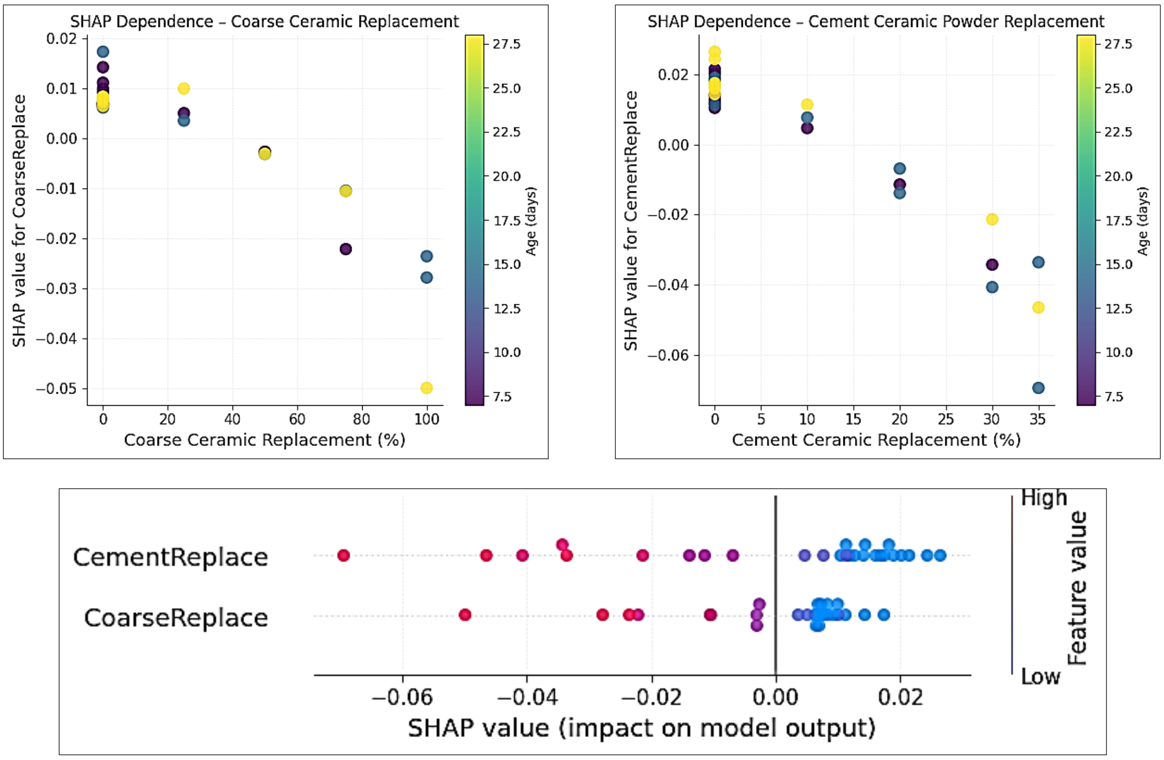


Fig. 8. SHAP for Flexural strength

3.4. Optimization and Sustainable Mix Design Implications

The final phase of this study focused on utilising the trained machine learning models to support optimisation and sustainable mix design of ceramic waste–based concrete. Based on the model results, Random Forest was selected to be used as the main predictive model. The Support Vector Regression was chosen as well for, scenario-based ranking since it is a smooth regression interpolation characteristic. This is due to the scenario-based predictions are limited by the size and structure of the experimental dataset. Therefore, they should be interpreted as exploratory rather than universally generalizable results. Furthermore, the scenario-based predictions generated using SVR should not be extrapolated beyond the experimentally investigated replacement ranges, as the model was calibrated exclusively using the available laboratory dataset. They were optimised based on three different scenarios as explained below. Also, the results of these three scenarios were shown in Table 7, 8 and 9.

In the first scenario, ceramic powder replacement was set at 0 percent, and the percentage of ceramic coarse aggregate was changed based on the values of experimental work. The model predictions reported that less to moderate amounts of ceramic aggregate substitution led to only marginal losses in compressive strength to the control mix. This implies that ceramic aggregate can be used as an effectively substitute to natural coarse aggregate without any serious weakness in the mechanical performance.

In the second case, the replacement of the ceramic coarse aggregate was set at 0%, and ceramic powder was a partial replaced for cement in increasing percentage. There was a stronger sensitivity of the model predictions with ceramic powder replacement as opposed to aggregate substitution in strength criteria. While low replacement levels gave satisfactory strength performance, increase of ceramic powder contents gave showed some losses of strength. This action is in line with SHAP-based interpretation, which showed ceramic powder replacement as a very potent parameter in controlling the strength development. The results of the optimisation process indicate that replacement of ceramic powders should be done with care, restricted to ensure mechanical performance in sustainable concrete design.

Table 7. Scenario I - ceramic aggregate replacement only

Coarse Replace (%)	Cement Replace (%)	Predicted Compressive Strength (MPa)	Coarse Replace (%)	Cement Replace (%)	Predicted Split tensile Strength (MPa)	Coarse Replace (%)	Cement Replace (%)	Predicted Flexure Strength (MPa)
14	0	27.459950	10	0	3.362374	14	0	3.586778
13	0	27.459906	11	0	3.362260	15	0	3.586732
15	0	27.459039	9	0	3.362254	13	0	3.586679
12	0	27.458854	12	0	3.361922	16	0	3.586547
16	0	27.457232	8	0	3.361895	12	0	3.586430
11	0	27.456738	13	0	3.361367	17	0	3.586227
17	0	27.454585	7	0	3.361288	11	0	3.586026
10	0	27.453507	14	0	3.360603	18	0	3.585778
18	0	27.451158	6	0	3.360429	10	0	3.585461
9	0	27.449110	15	0	3.359639	19	0	3.585207

Table 8. Scenario II - ceramic powder replacement only

Coarse Replace (%)	Cement Replace (%)	Predicted Compressive Strength (MPa)	Coarse Replace (%)	Cement Replace (%)	Predicted Split tensile Strength (MPa)	Coarse Replace (%)	Cement Replace (%)	Predicted Flexure Strength (MPa)
0	5	27.435250	0	0	3.349670	0	5	3.586600
0	4	27.434746	0	1	3.343528	0	6	3.586419
0	6	27.429668	0	2	3.336459	0	4	3.585736
0	3	27.426993	0	3	3.328758	0	7	3.585293
0	7	27.419197	0	4	3.320717	0	3	3.583736
0	2	27.410901	0	5	3.312622	0	8	3.583329
0	8	27.405042	0	6	3.304737	0	9	3.580638
0	9	27.388379	0	7	3.297307	0	2	3.580522
0	1	27.385483	0	8	3.290542	0	10	3.577332
0	10	27.370319	0	24	3.286949	0	1	3.576029

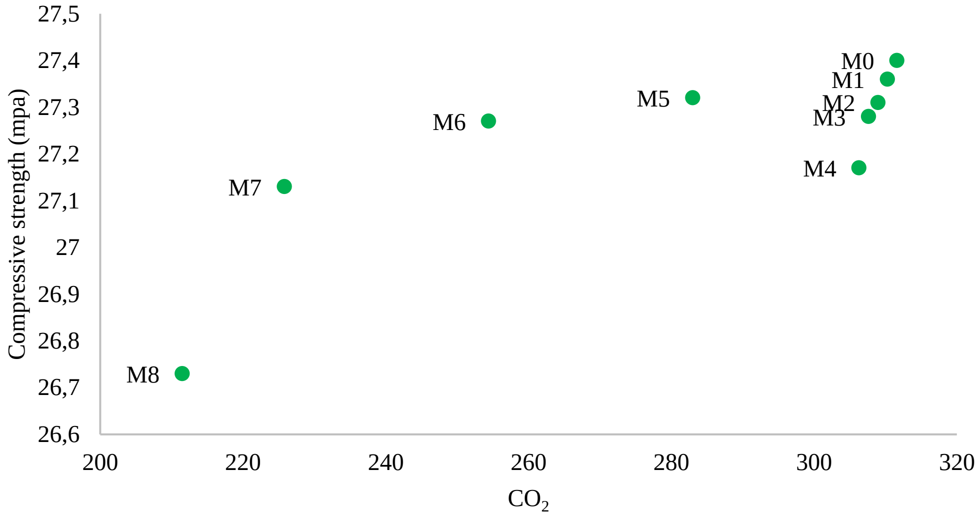
Table 9. Scenario III - combined ceramic aggregate and powder replacement

Coarse Replace (%)	Cement Replace (%)	Predicted Compressive Strength (MPa)	Coarse Replace (%)	Cement Replace (%)	Predicted Split tensile Strength (MPa)	Coarse Replace (%)	Cement Replace (%)	Predicted Flexure Strength (MPa)
10	5	27.526352	10	0	3.362374	10	5	3.600096
15	5	27.522104	15	0	3.359639	15	5	3.600010
5	5	27.499204	5	0	3.359312	20	5	3.596147
20	5	27.493183	20	0	3.352140	5	5	3.595775
15	0	27.459039	0	0	3.349670	25	5	3.589263
10	0	27.453507	25	0	3.341082	10	10	3.587372
25	5	27.447099	30	0	3.327746	15	0	3.586732
20	0	27.442203	10	5	3.324758	0	5	3.586600
0	5	27.435250	15	5	3.322155	10	0	3.585461
10	10	27.434625	5	5	3.321830	15	10	3.585224

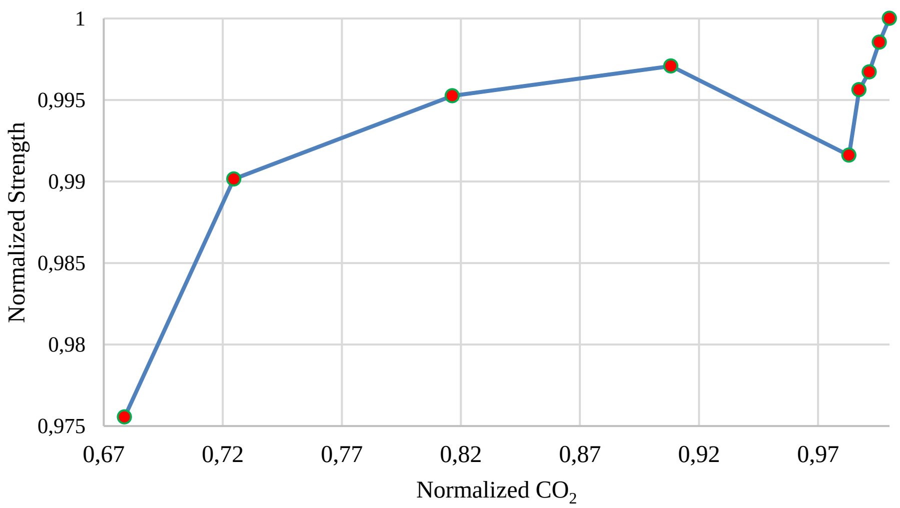
The third situation was simultaneous change of ceramic coarse aggregate and ceramic powder replacement percentages. Estimated strength rankings showed that combinations of moderate ceramic aggregate percentage and low ceramic powder substitution produced the most favourable performance. Replacement of these two parts in excess led to quality reductions, highlighting the interactive influence of aggregate quality and paste composition. The combinations of the scenarios produced by this analysis are ranked to provide a practical envelope of viable waste utilisation of ceramic that allow engineers to trade off mechanical performance to sustainable performance.

3.5. Sustainability–Performance Assessment

Figure 9(a) shows the relationship between embodied CO_2 emissions and 28-day compressive strength for all mix. The control mix (M0) exhibits the highest embodied carbon due to high OPC content and mixes with ceramic powder significantly reduces total CO_2 emissions. Mix M8 has the lowest embodied carbon with approximately 32% reduction in comparison with M0 and with a moderate reduction in compressive strength. Moderate cement replacement levels (M5–M7) show good CO_2 reduction with less compromise in compressive strength. This indicates that partial substitution of cement with ceramic powder can enhance environmental performance without lowering structural performance. However, ceramic coarse aggregate replacement exhibits comparatively less influence on embodied carbon, as aggregate production contributes significantly less CO_2 than cement manufacturing.



(a)



(b)

Fig. 9. (a) Embodies CO2 emission vs 28-day compressive strength (b) Sustainability – Strength trade off curve

Sensitivity analysis indicated that SPI variation was governed primarily by the cement emission factor. The sustainability trade-off curve in figure 9(b) shows the relationship between normalized compressive strength and normalized CO_2 emissions. As cement replacement increases normalized CO_2 decreases with normalized strength remains higher up to moderate replacements. After that it gradually starts declining at higher substitutions. Mixes with moderate ceramic powder replacement (10%-20%) exhibit SPI values greater than unity, indicating improved eco-efficiency compared to conventional concrete. Excessive cement replacement (>30%) has lower SPI valued due to its reduction in strength even with providing high environment benefits. This embodied carbon assessment was limited to small system boundary considering material production and processing stages per cubic meter of concrete. Transportation, construction, and end-of-life phases were not included. Therefore, this SPI is interpreted as a comparative eco-efficiency indicator rather than a comprehensive life-cycle sustainability metric. The SPI values are influenced by the selected embodied carbon emission factors and system boundary assumptions adopted in this study; however, the relative ranking of the investigated concrete mixtures remained consistent under the adopted assessment framework.

5. Conclusions

This research examined the mechanical properties of concrete that had ceramic waste as a mix substitution of natural rough aggregates and cement and optimized by ML modelling and explainable artificial intelligence methods. By integrating strength, structural threshold constraints, and embodied carbon quantification, the Sustainability–Performance Index provides a rational decision-support tool for sustainable mix selection. The use of multiple models is intended to provide comparative insight rather than to rely on a single model for all analytical purposes. According to the experimental program and further data-based analysis the following inferences can be made:

- The higher the replacement of ceramic aggregates, the higher the workability of the concrete. The workability decreased with the addition of ceramic powder due to its excellent absorption property. The strength of concrete decreases linearly with the increase in ceramic aggregate and cement, but the target strength is achieved. Concrete with 25% ceramic aggregate substituted for coarse aggregate outperformed the other mixes in terms of compressive strength, split tensile strength, and flexural strength. In the case of cement, the mixes up to 30% of ceramic powder can be used.
- Ensemble-based algorithms showed better predictive power among the assessed machine learning models. The most accurate compressive strength prediction is produced by Random Forest Regression, but Decision Tree-based models showed strong split tensile and flexural strength performance. Ceramic cement replacement has a stronger impact on strength variation than ceramic coarse aggregate replacement, according to SHAP interpretation. Several high-performing combinations of ceramic aggregate and ceramic powder replacement were found using model-based optimization rather than a single ideal mix.
- The sustainability – strength trade off analysis reveals that feasible eco-efficient performance is achieved within moderate replacement ranges rather than at maximum substitution levels. The embodied CO2 reduction is primarily governed by cement replacement levels.

The study concludes that cement substitution is the most influential factor for both strength and carbon reduction, whereas aggregate replacement contributes comparatively for both. Therefore, careful optimization of ceramic powder content is critical for achieving low-carbon concrete while maintaining mechanical performance.

The present study has certain limitations that should be acknowledged. First, durability-related properties such as water absorption, chloride penetration resistance, sulphate resistance, shrinkage, and long-term durability performance were not experimentally investigated. Therefore, the findings are restricted to fresh and mechanical properties of M20 grade concrete. Second, external validation using independent datasets was not performed because comparable ceramic waste concrete datasets developed under similar experimental conditions were not readily available. Third, the developed machine learning models were trained using data obtained from M20 grade concrete only; therefore, their applicability to higher-strength or specialty concrete mixtures should be interpreted with caution. Finally, deep learning approaches were not explored due to the moderate size of the experimental dataset. Future studies should address these limitations through durability assessment, external validation, investigation of multiple concrete grades, and implementation of advanced deep learning techniques

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