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INTERPRETING CONCRETE COMPRESSIVE STRENGTH THROUGH MIX PROPORTIONS AND CURING AGE

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Abstract:

The relationship between the compressive strength of concrete and the proportion of the mix and curing age of the concrete allows for understanding and a transparent interpretation of the concrete performance in the laboratory. These relationships were investigated in this study through experimental concrete data with 188 observations. Three repeats were removed and 185 observations were arranged into 47 operational mix groups. Descriptive analysis, correlation assessment, multiple linear regression and ridge regression techniques have been used and the degree of predictiveness assessed by grouped cross validation. The positive adjusted associations of total amount of binder with strength, and of the log of curing age with strength, and the negative associations of water/binder ratio and fly ash replacement fraction with strength were significant. The confidence intervals for GGBS, metakaolin and recycled aggregate fractions were found to contain zero. These values were 0.843 for ordinary regression, and 0.844 for ridge regression in the validation set, respectively. Logarithmic age gave better prediction than did untransformed age; there was no improvement provided by the tested composition–age interaction. Similar predictive outcomes were generated using sensitivity analyses. These results justify the use of interpretable regression for estimating the strength variation under specific conditions in the laboratory. However, since the predictions are dependent on one another, and the composition is limited, there is a lack of interpretability until it is separately validated prior to general use.

Keywords: *Concrete compressive strength, Mix proportions, Curing age, Regression analysis, Grouped cross-validation*

1. Introduction

The compressive strength of concrete is a key factor in determining its performance, which plays an important role in the design of structures, planning of construction, and evaluation of concrete quality. It relies on the joint effects of cementitious materials, water, aggregates, admixtures and curing conditions. These relationships are especially significant when using alternative materials to supplement or replace conventional ingredients. A statistical approach can be used to elucidate the influence of the strength observed on various mixture characteristics and can also be used to provide practical estimates of strength for compositions that have not been used before. The study of sustainable concrete has been followed by a regression study, which proves the relevance of establishing measurable material properties with the quantitative calculation of strength (Saxena et al., 2024).

The strength relationships among mix proportions cannot be expressed by any single proportion of the individual ingredients (Ghrici et al., 2025). If there is a variation in the amount of cementitious material, water content has different meanings, and if there is a change in binder composition but not in its total amount, replacement fractions can be used. Therefore, the representation of the predictors is a relevant analytical choice. Some studies that include mixture proportions, manipulated proportions and atmospheric parameters have shown the benefit of optimizing the information provided to predictive models, in addition to choosing the right algorithm. This helps to consider physically meaningful variables prior to the development of models (Akber, 2024).

The concrete strength can be interpreted with the dimensions of time when curing is used. The measurements taken in different ages can be different stages of the materials' development and can, if not taken into account, sometimes lead to misleading comparisons of different mixtures (George et al., 2026). In addition, the strength could not necessarily be linearly related to elapsed time over the entire observation period. Investigations of strength prediction at very early ages highlight the need for specifying the time interval over which a model is supposed to be valid. To assess composition–strength relationships, age needs to be explicitly represented (Peng et al., 2022).

The elapsed curing time is also a partial description of the curing conditions for strength development. Specimens tested at the same nominal age can be differentiated by their temperature history and moisture availability. The importance of the time–temperature data for early strength estimation is emphasized by the research, which compared the maturity-based assessment to artificial neural networks (Guo et al., 2023). If environmental measurements are not available, statistical models may be used to describe the variation of age, but they cannot remove all the environmental influences involved in curing. When evaluating the significance of the results and the generalizability of results from controlled lab-based observations to the construction context, this distinction is important.

With the help of machine learning, new methods for predicting concrete compressive strength have been developed, allowing the investigation of relationships between various material inputs. But these are two different kinds of research needs that are answered by predictive performance and by interpretability. A model can make a very accurate prediction of strength without giving a simple explanation of how the predictors go into the prediction. Where transparent comparisons between mix proportions are desired (Hamed et al., 2026), interpretable regression continues to be useful as a baseline. There is recent research on advanced prediction techniques that can give a wider context for assessing the value of using more complex models with the data that is available (Nikoopayan Tak et al., 2025).

Explanatory modeling is also gaining popularity in special concrete systems. Three-dimensional printed concrete research has been conducted on the relationships between binders and their proportions, highlighting the need to understand the relationship between material combinations in their given formulation (Hao et al., 2026). These studies encourage further investigation of composition-dependent relationships, however, results from these studies should not be blindly extrapolated to traditional or recycled-aggregate mixtures. The meaning of predictor effects can vary depending on the production process and the constituent systems involved. Interpretation should then be linked to the materials and experimental conditions that are shown in each data set (Abbas & Alsaif, 2025).

The methodological problem in the present investigation is how to identify the useful predictive relationships and how to avoid the unstable or redundant estimates of the coefficients. The total binder amount is mathematically related to the amounts of the constituents, and the water/binder ratio may still be highly correlated with the amount of binder. A second consideration is the random splitting of observations of similar compositions to yield a hopeful assessment for new mixes (Adamu et al., 2026), if similar mixes are observed repeatedly at different ages. These characteristics can be used to motivate a parsimonious predictor representation, an explicit analysis of collinearity, and a validation that maintains the grouping of related compositions.

This study therefore aims to investigate the concrete compressive strength for selected mix proportions and curing age using interpretable regression model. Ordinary regression yields adjusted association estimates and ridge regression yields a regularized comparison. The analysis includes descriptive exploration, uncertainty estimation and validation in groups according to mix composition (Hari & Zhuge, 2024). The significance of its contribution is in the evaluation of what these laboratory observations can contribute to understanding strength relationships and predictive performance; and what they say about unadjusted patterns versus conditional estimates. The study addresses the following objectives:

1. To characterize variations in concrete compressive strength across observed mix compositions and curing ages.
2. To quantify adjusted associations between selected mix proportions, curing age, and concrete compressive strength.
3. To compare regression model performance and interpretability using validation grouped by related concrete mix compositions.

2. Materials and Methods

2.1. Study Design and Data Source

The secondary analysis of the experimental data of concrete produced in the Indian Institute of Technology Bhubaneswar and archived in Mendeley data repository (Biswal et al., 2022) will be used in this study. There are 188 numbered observations of the concrete's characteristics, the age at which it was cured, and its compressive strength in the source. The results from several compositions will not be treated as separate independent mix designs since several of those compositions are repeated over time of curing. The analysis will examine associations between composition and strength, and test the validity of interpretable regression models, and only draw conclusions for materials and experimental conditions represented in the data.

2.2. Data Extraction and Quality Assessment.

Using Python, the PDF table will be transformed to a structured data set which will then be compared with the original document. Checks will highlight any missing items, errors in the extraction, any inconsistencies in the numerical precision, and any unreasonable values. Units of measurement and the use of abbreviations will be checked against existing source information. Before deciding on the analytical treatment, three identical pairs of observations need to be investigated. Water – cementitious material ratios will be recorded and compared with calculated ratios. Original entries will be kept and corrections, exclusions and unresolved discrepancies will be recorded, in order to ensure transparency and reproducibility.

2.3. Outcome and Predictor Specification

The continuous outcome variable will be compressive strength. Cement, fly ash, ground granulated blast-furnace slag, metakaolin, water, admixtures, natural aggregates, recycled aggregates, sand and curing age will be included as predictors in the candidate model. All of the total amount of cementitious material and the amounts of each of the cementitious materials will not be entered into ordinary regression at the same time because the mathematical dependence on each other causes redundancy. Physical relevance, observed variation and sample size will be taken into account when deciding which predictors to use. The continuous predictors that need to be standardized will be standardized only during the training folds. Only for data verification, serial numbers will be used as identifiers.

2.4. Exploratory and Association Analyses

Continuous variables will be summarized with means, standard deviations, medians, inter-quartile ranges and observed ranges using descriptive analysis. Frequency distributions will be used to describe the curing ages and categories of composition. Distributional characteristics will be explored, along with unusual observations and possible nonlinear relationships using histograms, boxplots and scatterplots. Pearson correlations will be used to summarize approximately linear associations, and Spearman correlations will be used to characterize monotonic associations as appropriate. The correlation estimates will be descriptive, as there may be dependency between observations with mix compositions. The exploratory findings will be used for parsimonious model specification but should not be used as evidence of causal effects.

2.5. Regressão e Interpretação

A baseline for estimating adjusted associations will be provided by multiple linear regression, which will be interpretable. To compare, you will use ridge regression which will have reduced coefficient instability caused by correlated predictors. Two untransformed and a log-scaled specification will be used to assess curing age. If supported by data coverage and physical reasoning a limited composition–age interaction will be considered. Inner grouped cross-validation (CV) will be used to select ridge penalties. Causal interpretations will not be made for coefficients, which will be interpreted based on predictor units, transformations and adjustment variables.

2.6. Diagnostics, Validation, and Sensitivity Analysis of a model

The following situations will be considered in model assessment: Residual patterns, unequal error variance, multicollinearity, and influential observations. Grouped cross-validation will be used to determine the predictive performance of the model, avoiding information leakage where there are related mix compositions. Predictive accuracy will be summarized in terms of mean absolute error, root mean squared error, and validation R^2. Baseline coefficients will be estimated using a bootstrap resampling technique of mix groups to obtain confidence intervals. Duplicate handling options and other age-specifications will be compared through sensitivity analyses. Software versions, grouping rules and random seeds will be documented; Python will support analysis.

3. Results

3.1. Data Quality and Analytical Sample

A total of 188 complete observations in 17 columns were found in the PDF. Three redundant, identical rows were removed, resulting in 185 observations in 47 operating mix groups. These groups were not necessarily different experimental batches but matched instead based on the composition of the base materials. Six curing ages were observed. There was one reported water/binder ratio that was different than the calculated ratio by more than 0.01. The quantities of water and total cementitious materials were then kept constant and the ratios recalculated accordingly. The summary of the sample preparation is presented in Table 1. Sensitivity to decisions was tested by analyses that eliminated duplicate entries from the data and by analyses of ratios derived from recorded data.

Table 1. Data Quality Assessment and Analytical Sample

Indicator	Value
Original observations	188
Original columns, including identifier	17
Missing numeric cells	0

Identical observation pairs	3
Excess identical rows excluded	3
Final analytical observations	185
Operational mix groups	47
Distinct curing ages	6
Absolute recorded–calculated ratio differences exceeding 0.01	1

3.2. Distribution of Mix Characteristics and Compressive Strength

The average of the 90 source units for the compressive strength was 34.25 with a standard deviation of 18.03 and a range of 6.00 to 73.76. The numbers of source units for mean cement and total cementitious material were 334.12 and 457.56, respectively. The following water/binder ratios were calculated: 0.2500 to 0.7522. Descriptive statistics are displayed in table 2. Figure 1 shows strength distribution with respect to curing ages. The differences between age groups should not be considered as strength trajectories within each mix, since there were differences in the composition of each age group. There were irregular observations as only 17 were taken at 14 and 56 days.

Table 2. Descriptive Statistics of Mix Characteristics and Compressive Strength

Variable	**Mean**	**SD**	**Minimum**	**Maximum**
Cement	334.119	143.315	113.000	680.000
Fly ash	50.811	101.884	0.000	385.000
GGBS	60.995	113.675	0.000	385.000
Metakaolin	11.632	26.910	0.000	102.000
Total cementitious material	457.557	144.624	226.000	680.000
Water	170.454	14.287	146.000	221.000
Calculated water/binder ratio	0.4213	0.1632	0.2500	0.7522
SP	2.518	2.320	0.000	6.600
VMA	0.340	0.498	0.000	1.380
Natural coarse aggregate, 20 designation	38.059	144.949	0.000	604.000
Natural coarse aggregate, 10 designation	37.654	143.407	0.000	598.000
Recycled coarse aggregate, 20 designation	386.378	127.221	0.000	516.000
Recycled coarse aggregate, 10 designation	484.497	148.642	0.000	633.000
Sand	647.622	81.127	516.000	815.000
Curing age	27.805	28.458	3.000	90.000
Compressive strength	34.252	18.025	6.000	73.760

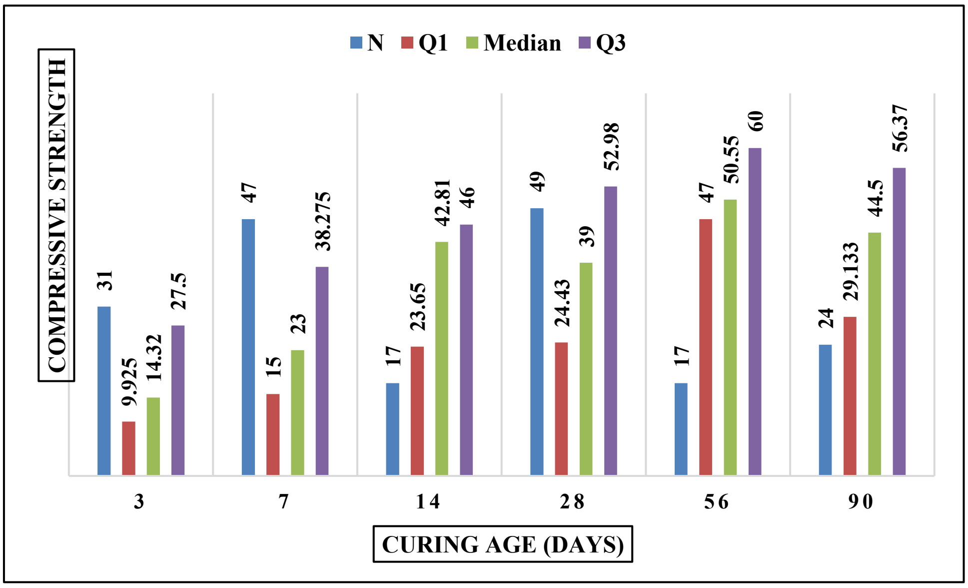

Figure 1. Distribution of Compressive Strength Across Curing Ages

3.3. Unadjusted Relationships with Compressive Strength

The calculated water/binder ratio was found to be negatively correlated with compressive strength while the total cementitious material was found to be positively correlated with compressive strength. Pearson's correlation coefficients were −0.666 and 0.709, respectively. The quantities of fly ash exhibited a negative correlation while quantities of GGBS and metakaolin exhibited positive correlation. The strength values increased with age, and Pearson and Spearman coefficients were 0.421 and 0.527, respectively. These exploratory relationships are summarized in Table 3. As the water/binder ratio increases in bands, so does the decreasing mean strength that is shown in Figure 2. They are not adjusted and could be different due to the difference in age, binder type and other mixture properties.

Table 3. Unadjusted Associations Between Selected Predictors and Compressive Strength

Predictor	N	Pearson r	Spearman ρ
Calculated water/binder ratio	185	−0.666	−0.649
Total cementitious material	185	0.709	0.684
Fly ash quantity	185	−0.269	−0.283
GGBS quantity	185	0.212	0.182
Metakaolin quantity	185	0.431	0.401
Curing age	185	0.421	0.527

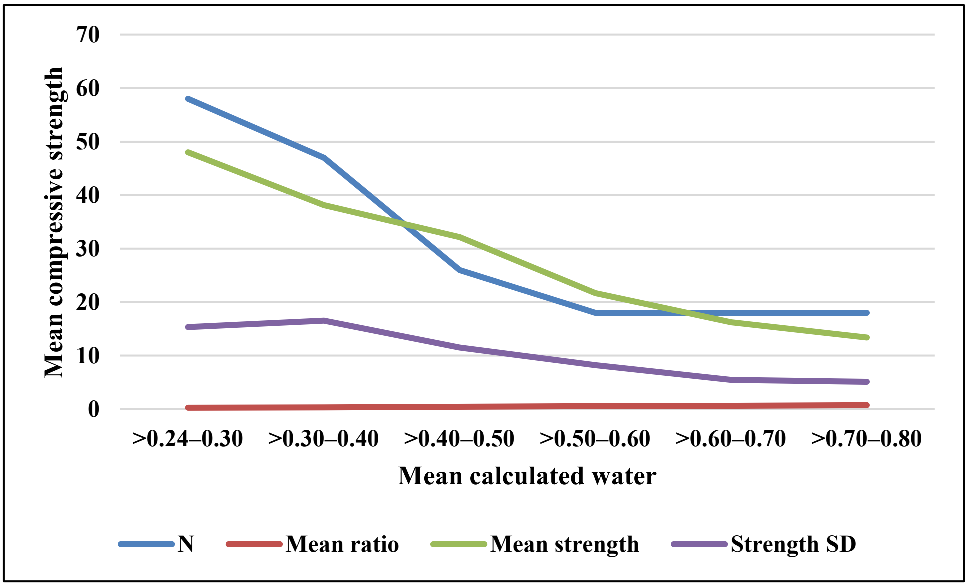

Figure 2. Mean Compressive Strength Across Water/Binder Ratio Bands

3.4. Adjusted Associations of Mix Proportions and Curing Age

Log curing age was adjusted, and was positively associated with the coefficient of 7.053 for a bootstrap interval of 6.076–8.161. The water/binder ratio and the fly ash fraction were found to be negatively correlated whereas the total binder was found to be positively correlated. The zero was included for the GGBS, metakaolin, and recycled aggregate fractions. These estimates are shown in Table 4. There were therefore no clear associations between the material quantities, and the corresponding adjusted fractions, when the material-quantity correlations were positive and unadjusted. Conditional strength prediction of selected observed compositions is shown in Figure 3. The exploratory fly ash–age interaction was not found to be useful for grouped predictive performance and was not retained.

Table 4. Adjusted Regression Estimates for Concrete Compressive Strength

Predictor and increment	**Coefficient**	**95% CI lower**	**95% CI upper**
Intercept	9.696	−16.642	36.380
Water/binder ratio: 0.10 increase	−3.128	−6.037	−0.294
Total binder: 100-source-unit increase	5.123	1.886	8.476
Fly ash fraction: 10-percentage-point increase	−4.298	−5.241	−2.646
GGBS fraction: 10-percentage-point increase	−0.627	−1.225	0.061
Metakaolin fraction: 10-percentage-point increase	2.704	−0.823	5.599
Recycled coarse aggregate fraction: 0 to 1	−0.471	−3.902	2.765
Natural logarithm of curing age: one-unit increase	7.053	6.076	8.161

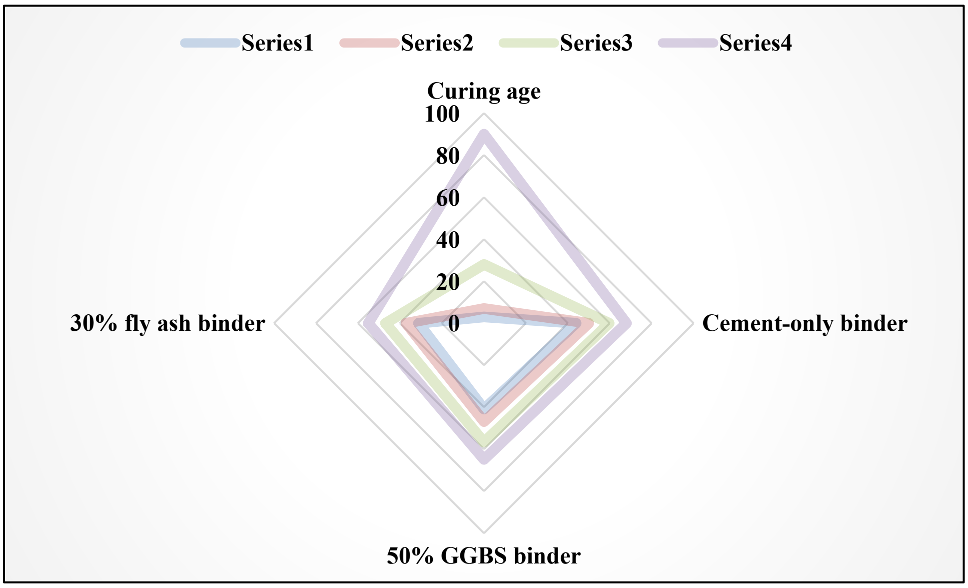

Figure 3. Model-Estimated Strength Development Across Selected Observed Mix Compositions

3.5. Predictive Performance and Robustness

The five-fold grouped validation results showed an RMSE value of 7.121 for ordinary regression and 7.090 for ridge regression, which were close to each other in terms of predictive ability. The R^2 values for the corresponding were 0.843 and 0.844 respectively. If the age was not transformed, the RMSE was 8.049. Errors of this prediction were very similar for duplicate retention and recorded-ratio analyses. Table 5 summarizes these comparisons. The maximum out-of-fold calibration and outlier distribution is shown in Figure 4 , where there is significant outlier presence with a maximum Cook's distance of 12.18 (10>4/N). Further testing is required to validate for general use.

Table 5. Grouped Validation Performance and Sensitivity Analysis Results

Model or sensitivity analysis	**N**	**Mix groups**	**MAE**	**RMSE**	**R^2**
Ordinary regression: log age	185	47	5.653	7.121	0.8431
Ridge regression: log age	185	47	5.635	7.090	0.8444
Ordinary regression: untransformed age	185	47	6.478	8.049	0.7995
Ordinary regression: fly ash × log-age interaction	185	47	5.696	7.233	0.8381
Ordinary regression: duplicate rows retained	188	47	5.613	7.076	0.8436
Ordinary regression: recorded water/binder ratio	185	47	5.668	7.143	0.8421

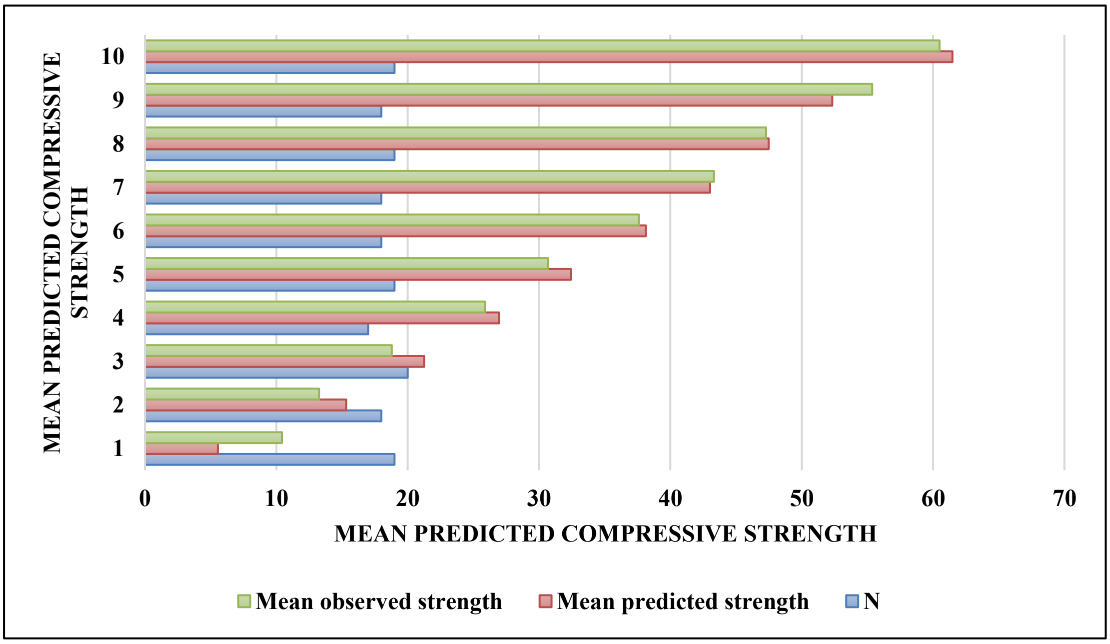

Figure 4. Out-of-Fold Calibration of Predicted Concrete Compressive Strength

4. Discussion

Measuring strength variation, making adjusted composition–age associations, and assessing prediction for held out mix groups. Total binder and the ratio of water/binder proved to be significant correlates in the unadjusted correlations, and were separated from other composition changes in the adjusted models. The log curing age showed a positive association while a few material fractions showed ambiguous coefficients. The performance of ordinary and ridge regression were comparable for grouped validation, suggesting a small benefit from regularization with the tested specification.

This focus on interpretable predictions is similar to the goal of explainable boosting, but the regression coefficients in the present work modelize linear associations in the conditional space, rather than flexible functions of the features responding to the output (Liu & Sun, 2023). The contribution is thus in terms of clear interpretation and evaluation of the observations that can be made, and not in the setting up of a "best possible" prediction algorithm.

The negative water/binder coefficient and positive total-binder coefficient indicate that strength was related to the ratio of the binder to the water. The maximum covariance inflation factor being 12.18 suggests high interdependence, however, and their separation is difficult to be exact. This concern is similar to the studies that looked at the conditional contribution of cement content, but the present analysis failed to suggest causal interpretation. (Adiguzel Tuylu et al., 2026)

Adjusted fly ash fraction continued to be negatively correlated with strength. This estimate assumes that all other observed compositions have a fixed total binder, but it does not guarantee that fly ash will affect performance in all cases (Liu et al., 2026). Fraction estimates were not considered to be valid after adjusting for the quantity of GGBS and metakaolin, as these relationships were positive before adjustment but became ambiguous afterwards.

The composition-dependent, non-linear relationships have also been found in bottom-ash-modified magnesium phosphate cement, and the strength of this cement diminishes as the water/cement ratio increases (Kabbo et al., 2025). It has a variety of binder chemistry that makes it impossible to directly measure effect magnitudes. Similarly, because of the unclear recycled-aggregate coefficient (Badeleh et al., 2026), it is not advisable to consider aggregate types as being equivalent on the basis of this coefficient, especially when compared to the limited data of natural aggregate comparison.

A positive coefficient of the log age means that the modeled strength is increasing for each day's increment. Logarithmic age also performed better than untransformed age in predicting the representation over the observed period, thus reinforcing this representation. This result is in line with the ensemble-model interpretation that curing age, water content and water/cement ratio are significant strength predictors (Kassa et al., 2026).

But the lower pooled median at 90 than at 56 days shows no evidence of deterioration of strength; different compositions were used for these groups. Conditional profile curves are used to compare in a more controlled way, but, as explained below, the age response is assumed in the additive model (Lv et al., 2025). Grouped prediction was not improved by the tested fly ash–age interaction and is not supported, with the exception of the evidence that it never modifies maturation. Such differences would need to be studied with more balanced observations over compositions and ages.

Grouped validation was employed, where related base compositions were grouped together and validation was done for held-out mix groups, instead of separating closely related records between the training and evaluation sets (Chen et al., 2026). The values of R^2 obtained here are around 0.84, which means that the data in this laboratory are useful for prediction. This slight distinction between ordinary and ridge regression does not prove the superiority of one or the other method.

The reported results of ensemble and neural network research in other concrete datasets have yielded better testing performance, such as the reported R^2 of 0.910, achieved using gradient boosting (Sharma et al., 2026). These values cannot be directly compared since the composition of the sample, the strength distribution (Palanisamy et al., 2025), and the design of the validation are different. Similarly, comparative research on geopolymer concrete is related to a different material system (Ezz & Bakr, 2026).

Transparently solving the coefficient matrix and checking the residual can be useful in practice for laboratory screening and to determine if a composition needs further testing. They cannot take the place of experimental strength verification or permit extrapolation outside the ranges of materials and ages observed.

The main drawback is the small number of mix groups in operation compared to the number of groups they appear to be. The 185 observations were from 47 groups, repeated compositions, unbalanced age coverage and restricted contrasts in aggregates. Group definitions were not necessarily experimental batches, but close approximations. Sensitivity analyses yielded similar prediction results from duplicate removal and ratio recalculation, but these do not address concerns with source records.

Collinearity and exclusion of 29 rank deficient bootstrap draws compounded the coefficient uncertainty. Interpretation and reproducibility are limited by the unreported environmental conditions, material characteristics and measurement units. External validation should come before practical deployment. An independent experimental test set was included in the recent framework along with uncertainty assessment, which gave a meaningful guideline for further assessment (Kassa et al., 2026). Balanced composition – age; documented batches; verified units and wider material sources should be included in future studies.

5. Conclusion

The relationship between concrete mix proportion, curing age and compressive strength was obtained for 185 observations in 47 operational mix groups. Positive adjusted associations were found with the total amount of binder and the curing age, while water/binder ratio and the fraction of fly ash replacement had a negative adjusted association for the compositions studied. The uncertainty over the estimation of the GGBS, metakaolin and recycled aggregate fractions was highlighted, and the difference between unadjusted correlations and conditional model coefficients was noted. Logarithmic transformation of the curing age provided a better prediction than the untransformed specification. The performance of ordinary regression and ridge regression were similar during the grouped validation, the R^2 value for ordinary regression is 0.843 and the R^2 value for ridge regression is 0.844 and the RMSE value for ordinary regression is 7.121 source units and RMSE value for ridge regression is 7.090 source units. Both with duplicate observations and with water/binder ratios recorded, the predicting results were similar. There was no improvement in the validation performance with the tested interaction of fly ash and age. The results confirm that interpretable regression is a suitable method to investigate the variation in laboratory strength and compositions that could be used for further experimental evaluation. However, there are limitations to coefficient interpretation and generalizability due to substantial predictor interdependence, limited independent composition information and the single-laboratory origin. The models provide descriptions of relationships in the data available and are not used to generate causal effects or optimal mixtures. Practical application should be preceded by a check of the measurement documentation, extension of the balanced composition–age testing and a test of predictions with independent laboratory data sets.

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