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Statistical Prediction of Concrete Compressive Strength Using Multiple Linear and Nonlinear Regression Models Developed in SPSS

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Abstract:
Compressive strength is crucial for assessing concrete quality, but traditional methods require a 28-day curing period. This study develops user-friendly statistical models for early strength prediction using SPSS software. Analyzing a database of 431 concrete mixtures (381 for calibration, 50 for validation), the study evaluated six key predictors. The full six-variable linear model achieved an R^2 of 0.628, while a non-linear log-age model improved fit to $R^2 = 0.650$ but lacked generalizability. Independent validation showed a 32–38% error margin due to dataset heterogeneity. Ultimately, cement content and water-cement ratio proved to be the most critical factors. The study concludes that SPSS-based regression provides a cost-effective early assessment tool, though more homogeneous datasets are needed for engineering-grade accuracy.

Keywords: concrete compressive strength; SPSS; multiple linear regression; correlation analysis; nonlinear regression; model validation; water-cement ratio.

التنبؤ الإحصائي بمقاومة الضغط للخرسانة باستخدام نماذج الانحدار الخطي وغير الخطي المتعدد المطورة بواسطة برنامج *SPSS*

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الملخص
تُعد **مقاومة الضغط** من أهم المؤشرات المستخدمة لتقييم جودة الخرسانة، إلا أن الطرق التقليدية لتحديدها تتطلب فترة معالجة تصل إلى **28يومًا** .تهدف هذه الدراسة إلى تطوير نماذج إحصائية سهلة الاستخدام للتنبؤ المبكر بمقاومة الخرسانة باستخدام برنامج **.SPSS**
اعتمدت الدراسة على تحليل قاعدة بيانات مكونة من **431 خلطة خرسانية،** حيث تم استخدام **381 خلطة لأغراض المعايرة (Calibration)**و **50 خلطة للتحقق .(Validation)**وقد تم تقييم ستة متغيرات رئيسية مؤثرة في مقاومة الضغط. أظهر

نموذج الانحدار الخطي الكامل الذي يعتمد على المتغيرات الستة معامل تحديد (R^2) بلغ **0.628**، بينما أدى نموذج الانحدار غير الخطي القائم على اللوغاريتم العمري إلى تحسين ملاءمة النموذج ليصل معامل التحديد إلى **0.650**، إلا أنه أظهر محدودية في القدرة على التعميم.
وأوضحت عملية التحقق المستقلة وجود هامش خطأ يتراوح بين **32–38%** نتيجة عدم تجانس مجموعة البيانات المستخدمة.
وفي النهاية، تبين أن **محتوى الأسمنت ونسبة الماء إلى الأسمنت** يمثلان أكثر العوامل تأثيرًا وأهمية في التنبؤ بمقاومة الضغط.

الكلمات المفتاحية: وتخلص الدراسة إلى أن نماذج الانحدار الإحصائي المعتمدة على برنامج **SPSS** توفر أداة اقتصادية وفعالة للتقييم المبكر لمقاومة الخرسانة، إلا أن تحقيق دقة بمستوى مناسب للتطبيقات الهندسية يتطلب استخدام قواعد بيانات أكثر تجانسًا وشمولًا.

1. Introduction

1.1 Background

Concrete is the most widely used construction material in the world, forming the structural backbone of buildings, bridges, dams, and industrial facilities. Its compressive strength is the single most important mechanical property used to judge whether a given batch or structural member meets its design requirements [1,2]. Compressive strength is usually obtained by casting standard cubes or cylinders and testing them after a 28-day curing period, according to international standards such as ACI, ASTM, and EN. This delay between casting and strength confirmation presents a long-term practical problem: any defect discovered after 28 days can lead to costly demolition, repair, or strengthening work and can disrupt the construction program [3,4].

Standards such as ACI 318 and EN 206 define statistical acceptance criteria for concrete based on the mean and characteristic values (typically the fifth percentile) of compressive strength results after 28 days from a random mix sample, in addition to minimum requirements for individual results. ASTM C39, on the other hand, specifies the corresponding standard test method for compressive strength of cylindrical samples. These acceptance frameworks are inherently retrospective, assessing conformity only after the curing period is complete. This is precisely the gap that early statistical prediction, of the type developed in this study, aims to bridge at the level of proactive and informal quality control, rather than formal standard compliance.

In recent years, machine learning and artificial intelligence techniques have been widely applied to predict the compressive strength of concrete from mix proportions, often achieving high accuracy [1, 2]. However, these models typically require programming skills, specialized software, and computing resources that are not always available to site engineers or quality control personnel working under tight project deadlines [4, 2]. This creates a practical gap between the latest predictive research and its practical application on construction sites or mixing plants.

SPSS (Statistical Package for the Social Sciences) offers a compromise: it provides descriptive statistics, correlation analysis, and regression modeling through a graphical interface familiar to most civil engineering graduates, and it produces clear and transparent regression equations instead of the opaque model weights [5, 6]. This transparency allows the resulting equation to be applied directly using a manual calculator or a simple spreadsheet, which is convenient for routine engineering practices.

1.2 Problem Statement

Predicting concrete compressive strength accurately is inherently difficult because strength development depends on a large number of interacting parameters – the water-cement ratio, cement content, aggregate proportions, curing age, and curing conditions, among others. Traditional testing captures only the outcome after 28 days and therefore cannot support real-time decisions during placement. There remains a need for simple, transparent, and reasonably reliable statistical tools that site and quality-control engineers can use to obtain an early estimate of concrete strength directly from mix design data, without requiring specialized computational infrastructure.

1.3 Objectives

The objectives of this study are to: (1) quantify the statistical relationships between key mixture variables and concrete compressive strength using correlation analysis; (2) develop and compare multiple linear regression models built from different combinations of predictor variables; (3) evaluate whether a nonlinear transformation of curing age improves predictive performance; (4) validate the selected model(s) against an independent dataset and quantify their prediction error; and (5) provide practical recommendations for the use of SPSS-based regression as a decision-support tool in construction quality control.

1.4 Significance and Scope

An accurate, easily applied prediction tool would allow site engineers and ready-mix producers to assess concrete quality at early ages, inform formwork-striking and load-application decisions, and flag mixtures likely to fail acceptance criteria before the full 28-day period has elapsed, thereby reducing rework, cost, and schedule risk [4]. The scope of the present study is limited to normal-strength, normal-weight concrete without supplementary cementitious materials or chemical admixtures, using six routinely recorded mix-design variables: cement content, water content, water-cement ratio, fine aggregate content, coarse aggregate content, and curing age.

1.5 Applications of Compressive Strength Prediction

Reliable early-age prediction models have several practical applications in construction practice: real-time quality control of individual batches at ready-mix plants; optimisation of mix designs to balance strength, cost, and sustainability; evaluation of alternative or recycled materials before full-scale adoption; and improved productivity in precast concrete production, where early demoulding decisions depend on early-age strength gain. Prediction at very early ages (3 and 7 days) is particularly valuable for determining safe formwork-striking times and for pacing construction activities on both residential and commercial projects [4].

1.6 Approaches to Compressive Strength Prediction

Broadly, three families of approaches have been used to predict concrete compressive strength. Theoretical methods rely on closed-form mathematical relationships linking strength to concrete composition and specimen geometry, typically derived from first principles or classical empirical laws such as Abrams' water-cement ratio law. Experimental methods rely on standard laboratory testing of cubes or cylinders at multiple curing ages and are the basis against which any predictive model must ultimately be validated. Numerical (statistical and machine-learning) methods, of which SPSS-based multiple linear regression is one example, use computational data analysis to establish empirical relationships between mixture variables and measured strength, and range in complexity from simple linear regression to deep learning. The present study sits within this third family, deliberately favouring the simplest, most transparent numerical technique (multiple linear regression) that remains compatible with routine site and quality-control practice.

1.7 Factors Influencing Concrete Compressive Strength

Beyond the six variables modelled explicitly in this study, the wider literature identifies a number of additional factors that influence compressive strength and that provide useful context for interpreting the present results. The water-cement ratio governs the porosity of the hardened cement paste and is generally regarded as the single most influential factor, with strength decreasing as the ratio increases. Cement content improves inter-particle bonding and cohesion, generally raising strength as content increases. Curing age reflects the progress of hydration, with most strength gain occurring within the first 28 days but continuing, at a decreasing rate, well beyond that period. The proportion of fine to total aggregate affects workability, density, and gradation, while the cement-to-aggregate ratio affects the bond between the cement paste and the aggregate particles. Supplementary cementitious materials (such as fly ash, ground granulated blast-furnace slag, or silica fume) and chemical admixtures (particularly superplasticisers, which allow water content to be reduced without compromising workability) can further modify strength development but were not present in the compiled dataset and are therefore outside the scope of the regression models developed here. Air content, specimen shape and size, and curing conditions (temperature, humidity, and curing method) are additional recognised influences that were not separately recorded in the source studies and are, together with the unmodelled material and procedural differences discussed in Section 5.2, a plausible contributor to the residual (unexplained) variance in the calibrated models.

1.2 Problem Statement

Accurately predicting concrete compressive strength is inherently challenging because strength development depends on many interrelated factors, such as the water-cement ratio, cement content, aggregate proportions, curing time, and curing conditions. Traditional tests only record the final result after 28 days and therefore do not support real-time decision-making during pouring. Thus, site engineers and quality control personnel need simple, transparent, and relatively reliable statistical tools to obtain an early estimate of concrete strength directly from mix design data, without requiring specialized computer infrastructure.

1.3 Objectives

This study aims to: (1) identify the statistical relationships between the main mix variables and concrete compressive strength using correlation analysis; (2) develop and compare multiple linear regression models based on different combinations of predictive variables; (3) evaluate whether a nonlinear transformation of the curing time improves predictive performance; and (4) validate the selected model(s) using an independent dataset and determine the prediction error. (5) Provide practical recommendations for using SPSS-based regression analysis as a decision-support tool in construction quality control.

1.4 Significance and Scope

A precise and easy-to-apply forecasting tool enables site engineers and ready-mix concrete producers to assess concrete quality in its early stages, guide formwork removal and load application decisions, and identify mixes likely to fail acceptance criteria before the full 28-day curing period, thus reducing rework, costs, and the risk of schedule delays [4]. The scope of this study is limited to ordinary compressive strength and weight concrete without additional cementitious materials or chemical admixtures, using six routinely recorded mix design variables: cement content, water content, water-to-cement ratio, fine aggregate content, coarse aggregate content, and curing age.

1.5 Applications of Compressive Strength Prediction

Reliable early-stage forecasting models have numerous practical applications in construction: real-time quality control of individual batches in ready-mix concrete plants; optimization of mix designs to balance strength, cost, and sustainability; and evaluation of alternative or recycled materials before their widespread adoption. Improving productivity in precast concrete production is crucial, as early formwork removal decisions depend on strength gain in the early stages. Predicting at very early stages (3 and 7 days) is particularly valuable for determining safe formwork removal times and regulating the pace of construction activities in both residential and commercial projects [4].

1.6 Compressive Strength Prediction Methods

Generally, three sets of methods have been used to predict the compressive strength of concrete. Theoretical methods rely on closed mathematical relationships that link strength to the concrete composition and the form of the sample, and are usually derived from fundamental principles or classical empirical laws such as Abrams' water-cement ratio. Experimental methods rely on standard laboratory tests of cubes or cylinders at various curing stages, which serve as the basis for validating any predictive model. Numerical methods (statistical and machine learning techniques), including multiple linear regression using SPSS software, employ computer data analysis to determine the empirical relationships between mix variables and measured compressive strength. Their complexity ranges from simple linear regression to deep learning. This study falls into this third category, deliberately favoring the simplest and most transparent numerical techniques (multiple linear regression) that align with routine site practices and quality control.

1.7 Factors Affecting Concrete Compressive Strength

In addition to the six variables explicitly modeled in this study, previous research indicates several additional factors influencing compressive strength, providing a useful context for interpreting the current results. The water-to-cement ratio controls the porosity of the hardened cement paste and is generally considered the most influential factor, with strength decreasing as this ratio increases. Cement content improves bonding and cohesion between particles, generally leading to increased strength as the content increases. Curing time reflects the progression of the hardening process, with most strength gain occurring within the first 28 days, but continuing, at a decreasing rate, for a considerable period thereafter. The ratio of fine aggregate to total aggregate affects workability, density, and gradation, while the cement-to-aggregate ratio influences the bonding between the cement paste and the aggregate particles. Supplementary cementitious materials (such as fly ash, ground granulated blast furnace slag, or silica fume) and chemical additives (especially superplasticizers, which allow for a reduction in water content without affecting performance) are used.

2. Literature Review

A large body of research has explored the prediction of concrete compressive strength using statistical and computational methods, and this section compiles the studies most relevant to the SPSS-based regression approach adopted here.

2.1 Regression-Based Prediction Using SPSS

Several studies have specifically used SPSS to construct multiple linear regression equations relating mix ratios to compressive strength. Hussein et al. [7] developed a multiple linear regression equation for high-strength concrete based on cement and water content. They reported a very strong correlation ($R = 0.974$, $R^2 = 0.949$) on a dataset of 56 cubic samples. Idris and Bello [8] modeled strength as a function of water-to-cement ratio and cement content within the range $W/C = 0.40–0.70$ and also reported a strong correlation. Unamba et al. [9] and Seif et al. [10] applied SPSS regression to smaller, specially designed datasets (36 and 14 mixes, respectively) and obtained models with a low prediction error on their own data. Behaqi and Rolia [11] used a ten-year laboratory record of 28-day strength results to construct an SPSS-based decision support model for quality control. A common feature of this group of studies is that the datasets were small and derived from a single laboratory or a narrow mixed design scope, resulting in very high R^2 values that may not be generalizable to more varied conditions.

2.2 Early Regression and Correlation Studies

Earlier foundational work established the statistical basis for strength prediction from mix proportions. Namyong et al. [12] used correlation analysis to identify water-cement ratio and cement content as the dominant predictors and derived regression equations from 7- and 28-day data. Pande and Gupta [13] confirmed experimentally that the water-cement ratio is the single most influential parameter governing strength development. Jee et al. [14] analysed 1,442 in-situ test results from 59 mixtures and showed that multiple linear regression using water-cement ratio, cement content, and the cement-to-aggregate ratio provides a practical quality-control tool. Neville [15] provides the classical theoretical basis linking the water-cement ratio to compressive strength through the porosity of the hardened cement paste.

2.3 Larger Databases and Comparative Studies

More recent studies have used considerably larger and more heterogeneous databases, which is directly relevant to the pooled dataset used in the present work. DeRousseau et al. [16] combined 1,681 field-produced mixtures with over 1,000 laboratory mixtures and found that even the best-performing regression and polynomial models achieved only a moderate coefficient of determination ($R^2 \approx 0.51$) when predicting field strength, and that models trained purely on laboratory data over-estimated field strength due to uncontrolled site conditions. Young et al. [17] used a database of more than 10,000 observations and found that machine-learning models outperformed classical regression for large, heterogeneous datasets, while still confirming cement content, water content, and age as dominant predictors. Assegie et al. [18] and Bansal et al. [19], working with the widely used UCI concrete dataset (1,030 records), reported R^2 values around 0.90–0.94 for optimised regression and machine-learning models, again identifying cement content, curing age, and water content as the most influential variables.

2.4 Nonlinear and Machine-Learning Approaches

Because strength gain with curing age follows a diminishing-returns pattern rather than a straight line, several studies have explored nonlinear formulations. Jaskulski et al. [20] built five first-order models with two to six input parameters and found that prediction accuracy improved as aggregate quality and additional variables were incorporated. Hematibahar and Kharun [21] compared linear, ridge, and polynomial regression on more than 45 mix designs and found ridge and polynomial regression outperformed ordinary linear regression ($R^2 = 0.93$ and 0.91, respectively). Wang et al. [22] and Ahmed et al. [23] used probabilistic and neural-network-based approaches on smaller, curated datasets and achieved very high R^2 values (0.966 and 0.977), reinforcing the general finding that model accuracy tends to improve as dataset homogeneity increases, even when the underlying mathematical form is comparatively simple.

2.5 Additional Experimental and Statistical Studies

A wider set of experimental and mixed experimental-statistical studies further substantiates the variables selected for this work. Ahn and Fowler [27] and Galetakis and Raka [28] examined the substitution of natural sand with manufactured or alternative fine aggregate fractions (7–18% and 20–40% respectively) and confirmed that fine-aggregate proportioning directly affects workability and hardened-state compressive strength, supporting the inclusion of sand content as an independent variable in the present models. Lamb [29] and Bahoria and Viragade [30] studied sand replacement materials in structural concrete across multiple strength grades (M20, M30, M40) and curing periods (7, 14, 28, and 90 days). Bahoria and Viragade explicitly used SPSS to generate mathematical models for predicting strength, confirming the validity of the software used here.

Kazberok and Lelusz [31] and Abd et al. [32] developed regression models relating strength to replacement ratios and curing periods for both cement paste and concrete, reporting strong correlation coefficients that reinforce the role of curing period as a predictor. [33] They applied full quadratic response surface models to cement and water content and found that quadratic boundaries improved the fit compared to simple linear boundaries at early ages (3, 7, and 28 days), which is consistent with the results of the current study indicating that nonlinear (logarithmic) age treatment improves calibration fit. Ramogade [34] compared multiple regression with conventional estimation at 3, 7, and 28 days and found that the regression-based prediction was more accurate, while Balika et al. [35] developed regression equations from four ratio-based predictors (water/cementite, fine aggregate/cementite, coarse aggregate/cementite, and cement content) that were validated at 28, 56, and 91 days, an approach conceptually similar to the ratio-based model 3 developed in the current study.

Sayed-Ahmed [36] constructed a statistical model based on water, cement, aggregate, sand content, and curing age. This model showed strong agreement with experimental results, accurately reflecting the set of variables used here. More recent applied studies, including those by Wang et al. [24], Ismail et al. [37], Izenkwah et al. [38], and Ramadan and Raharjo [39], emphasize the importance of cement content, water-cement ratio, and curing age as first-order predictors, extending the methodology to include machine learning and rapid quality assessment (less than 28 days), reflecting the motivation behind the strong early prediction mentioned in Section 1.1.

2.6 Synthesis and Research Gap

In this area of research, three consistent patterns emerge: (a) the water-to-cement ratio and cement content are among the strongest predictors of compressive strength; (b) curing age has a positive but non-linear effect; and (c) the accuracy of the reported model is strongly influenced by the size and homogeneity of the dataset. Small, single-source datasets tend to yield very high R^2 values, while large, multi-source aggregated datasets, such as those presented by DeRosso et al. [16], yield more moderate values, which are more likely to better represent the predictive performance in practice. This study addresses this gap by pooling 431 records from several previously published mixes, intentionally reflecting the variability a practicing engineer might encounter, and by validating the resulting regression models in SPSS using an independent sample, rather than relying solely on the R^2 value of the calibration set.

3. Materials and Methods

3.1 Data Collection

A database of 431 concrete compressive strength test results was compiled from previously published experimental studies, covering a wide range of mix proportions and curing times. Of these results, 381 (88%) were used to calibrate regression models and perform statistical analyses, while the remaining 50 (12%) were retained without prior review for independent model validation. The recorded variables included cement content, water content, water-cement ratio, fine aggregate (sand) content, coarse aggregate (gravel) content, curing time, and corresponding compressive strength. Curing times ranged from 1 day to 180 days, and the measured compressive strength values ranged from 9 to 79.99 MPa, reflecting a broad spectrum of concrete mixes, from ordinary to high-strength.

3.2 Variables

Table 1. *Variables used in the statistical analysis*

Variable	Symbol	Unit	Type
Cement content	C	kg/m³	Independent
Water content	W	kg	Independent
Water-cement ratio	W/C	–	Independent
Fine aggregate	FA	kg/m³	Independent
Coarse aggregate	CA	kg/m³	Independent
Curing age	Age	days	Independent
Compressive strength	f′c	MPa	Dependent

3.3 Statistical Analysis Procedure

All analyses were performed using IBM SPSS Statistics software. The process followed four stages.

3.3.0 Software and reproducibility

All calculations were performed in IBM SPSS Statistics using the built-in procedures Descriptives, Correlate-Bivariate, and Regression-Linear, following the step-by-step list sequences summarized for each stage below, so that any engineer with access to the same dataset and a standard SPSS license can reproduce the analysis without having to write custom scripts.

3.3.1 Descriptive statistics

Descriptive statistics (minimum, maximum, mean, and standard deviation) were calculated for all seven variables to characterize the dataset and confirm its suitability for regression analysis.

3.3.2 Correlation analysis

Pearson correlation coefficients were calculated for each pair of variables to determine the strength and direction of the linear correlation, identify the predictive variables most strongly associated with compressive strength, and detect multiple linear correlations between independent variables before regression modeling. Pearson's correlation coefficient, r, ranges from -1 (perfect negative linear correlation) to +1 (perfect positive linear correlation), with values close to zero indicating weak or no linear relationship. Statistical significance was assessed at the 0.01 and 0.05 levels using a two-tailed t-test, in accordance with SPSS output standards.

3.3.3 Multiple linear regression

Three alternative multiple linear regression (MLR) models were developed using the Enter method, each retaining a different combination of predictors, in order to examine the sensitivity of the fit to variable selection and to test for redundancy between cement content, water content, and the water-cement ratio (which is itself a function of the other two):

Model 1 (full model): $f'c = \beta 0 + \beta 1(C) + \beta 2(W/C) + \beta 3(W) + \beta 4(FA) + \beta 5(CA) + \beta 6(Age)$

Model 2 (W/C excluded): $f'c = \beta 0 + \beta 1(C) + \beta 2(W) + \beta 3(FA) + \beta 4(CA) + \beta 5(Age)$

Model 3 (C and W excluded): $f'c = \beta 0 + \beta 1(W/C) + \beta 2(FA) + \beta 3(CA) + \beta 4(Age)$

3.3.4 Nonlinear regression

Because strength gain with age is known to be nonlinear, curing age was transformed using the natural logarithm (Log_Age = LN(Age)) via the SPSS Compute Variable function, and this transformed variable replaced Age in an otherwise identical six-variable regression, to test whether a logarithmic age term improves the coefficient of determination relative to the linear-age Model 1.

3.3.5 Model validation

Regression equations for the three calibrated linear models were applied to the 50 validation records saved in a spreadsheet. Predicted force values were compared to the corresponding measured values, and three complementary error metrics were calculated for each model: mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). Both MAE and RMSE express the average prediction error in physical units of the response variable (MPa), noting that RMSE penalizes larger errors more significantly than MAE due to its error-squared-based formulation. As for MAPE, the same information is expressed as a percentage of the measured value, allowing the error to be interpreted independently of the absolute power level, and facilitating comparison with error statistics reported by other studies in Section 2. The Pearson correlation coefficient was also calculated between the predicted and measured validation values as an additional check of overall agreement.

3.4 Assumptions and Limitations of the Method

Multiple linear regression assumes a nearly linear relationship between each predictor and dependent variable, independence of residuals, homogeneity of variance (consistency of residual variance), and a nearly normal distribution of residuals. Because the dataset was compiled from multiple independent studies, rather than a single controlled experimental program, some of these assumptions are only approximately held. The resulting coefficient estimates should be interpreted as describing population-wide trends across the sampled mixtures, not as an exact physical law applicable to any single mixture. This limitation, and its implications for interpreting the coefficient of determination (R^2) and validation error values discussed in Sections 4 and 5, is a deliberate feature of the study design, not an oversight. The aim was to test the regression methodology available in SPSS under realistic, heterogeneous conditions, rather than ideal, single-source conditions.

4. Results

4.1 Descriptive Statistics

Table 2 summarizes the descriptive statistics for the calibration dataset (number of 381). The dataset covers a wide range of admixture ratios and ages, which is suitable for constructing a regression model applicable to large scales, although it also indicates greater dispersion than expected from a single-source dataset.

Table 2. *Descriptive statistics of the calibration dataset (n = 381).*

Variable	Minimum	Maximum	Mean	Std. Deviation
Cement (kg/m³)	270.0	758.0	354.45	66.30
Water (kg)	109.0	239.0	170.06	20.73
W/C (–)	0.15	0.70	0.487	0.077
Sand (kg/m³)	390.0	789.0	679.91	58.58
Gravel (kg/m³)	780.0	1291.0	1118.90	54.97
Age (days)	1	180	50.72	59.79
Compressive strength (MPa)	9.00	80.00	30.67	14.29

4.2 Correlation Analysis

Table 3 presents the Pearson correlation coefficients between compressive strength and each independent variable. Cement content showed a moderate positive correlation with strength ($r = 0.411$, $p < 0.01$), confirming that increasing cement content tends to raise strength. The water-cement ratio exhibited the strongest relationship of all the predictors, a strong negative correlation ($r = -0.657$, $p < 0.01$), consistent with the classical Abrams' law and with the wider literature reviewed in Section 2. Water content and sand content both showed moderate negative correlations with strength ($r = -0.384$ and $r = -0.385$ respectively, $p < 0.01$), while gravel content showed a weaker negative correlation ($r = -0.218$, $p < 0.01$). Curing age showed a weak but statistically significant positive correlation ($r = 0.129$, $p < 0.05$), reflecting ongoing hydration, though its comparatively low coefficient in this pooled dataset indicates that age effects are partly confounded by the wide range of mixtures sampled at different ages.

Table 3a. *Pearson correlation coefficients with compressive strength (n = 381)*

Predictor	Pearson r	Sig. (2-tailed)	Relationship
Cement content	0.411	0.000	Moderate positive
Water-cement ratio	−0.657	0.000	Strong negative
Water content	−0.384	0.000	Moderate negative
Sand content	−0.385	0.000	Moderate negative
Gravel content	−0.218	0.000	Weak negative
Curing age	0.129	0.012	Weak positive

Because cement content, water content, and the water-cement ratio are mathematically related, moderate inter-correlations were also observed among the predictors themselves (e.g., cement content and W/C: $r = -0.687$), motivating the alternative variable combinations tested in Models 2 and 3. The full inter-variable correlation matrix is presented in Table 3b.

Table 3b. *Full Pearson correlation matrix among all study variables (n = 381).*

Variable	Cement	W/C	Water	Sand	Gravel	Age	f′c

Cement	1.000	−0.687	0.303	−0.492	−0.336	−0.180	0.411
W/C	−0.687	1.000	0.394	0.262	0.306	0.173	−0.657
Water	0.303	0.394	1.000	−0.246	0.280	−0.009	−0.384
Sand	−0.492	0.262	−0.246	1.000	0.158	0.156	−0.385
Gravel	−0.336	0.306	0.280	0.158	1.000	0.052	−0.218
Age	−0.180	0.173	−0.009	0.156	0.052	1.000	0.129
f'c	0.411	−0.657	−0.384	−0.385	−0.218	0.129	1.000

The moderate correlations between cement content and both the water-cement ratio ($r = -0.687$) and sand content ($r = -0.492$) reflect the fact that these variables are not sampled independently in the pooled dataset but instead follow the proportioning conventions typically used in mix design. This partial redundancy is consistent with the near-identical performance of Models 1 and 2 discussed in Section 4.3 and is a normal feature of observational, literature-compiled datasets rather than a data-quality defect.

4.3 Multiple Linear Regression Models

Model 1 (full six-variable model)

The full model, including all six predictors, produced the equation:

$$f'c = 79.310 + 0.099(C) - 20.096(W/C) - 0.425(W) - 0.086(FA) + 0.048(CA) + 0.065(Age)$$

Table 4. *Summary statistics for Model 1, Model 2, and Model 3 (calibration set, n = 381).*

Model	Predictors retained	R	R^2	Adj. R^2	Std. Error (MPa)	F	Sig.
Model 1	C, W/C, W, FA, CA, Age	0.792	0.628	0.622	8.786	105.22	0.000
Model 2	C, W, FA, CA, Age	0.792	0.627	0.622	8.786	126.06	0.000
Model 3	W/C, FA, CA, Age	0.745	0.555	0.550	9.584	117.23	0.000

The results show that Model 1 and Model 2 achieved essentially identical explanatory power ($R^2 \approx 0.627$–0.628), despite Model 2 omitting the water-cement ratio entirely; this confirms that most of the predictive information carried by W/C is already contained in the separate cement and water terms, and that the water-cement ratio coefficient in Model 1 was not statistically significant ($t = -1.006$, $p = 0.315$), unlike the individually significant cement and water terms. Model 3, which excluded cement and water content and retained only W/C together with the aggregate and age terms, produced a visibly weaker fit ($R^2 = 0.555$), indicating that cement and water content jointly carry more information than the ratio alone once aggregate proportions are already in the model.

Table 5. *Regression coefficients for Model 1 (dependent variable: compressive force).*

Predictor	B	Std. Error	Beta	t	Sig.
(Constant)	79.310	20.749	–	3.822	0.000
Cement (C)	0.099	0.025	0.460	4.009	0.000
Water-cement ratio (W/C)	−20.096	19.966	−0.108	−1.006	0.315
Water (W)	−0.425	0.062	−0.617	−6.860	0.000
Sand (FA)	−0.086	0.009	−0.354	−9.656	0.000
Gravel (CA)	0.048	0.012	0.185	4.067	0.000
Age	0.065	0.008	0.270	8.375	0.000

Physically, the positive cement coefficient (B = 0.099) and negative water coefficient (B = −0.425) in Model 1 correspond to the fundamental role of the water-cement ratio in controlling the porosity of the hardened cement paste: at a constant water content, additional cement improves the paste-to-voids ratio and increases strength, while at a constant cement content, additional water dilutes the paste and increases capillary porosity, thus reducing strength. The positive age coefficient (B = 0.065) reflects the continuous hydration process, and the negative sand coefficient and positive gravel coefficient correspond to the effect of aggregate gradation and fill density on the strength of the hardened material. The water-to-cement ratio term was not statistically significant once cement and water were entered separately ($p = 0.315$), which is expected given the strong linear correlation between W/C and its constituent variables (Table 3b). This does not indicate that the water-to-cement ratio is not physically important, but only that its explanatory contribution has already been captured by the separate C and W terms.

Model 2 (five-variable model, W/C excluded)

$$f'c = 63.208 + 0.123(C) - 0.482(W) - 0.086(FA) + 0.055(CA) + 0.064(Age)$$

All five retained predictors were statistically significant ($p < 0.001$), and the standardised coefficients (Beta) show water content (−0.700) and cement content (0.569) as the two dominant influences on predicted strength, followed by age (0.269), sand (−0.353), and gravel (0.211). Removing the collinear water-cement ratio term allowed the cement and water coefficients to be estimated with smaller standard errors than in Model 1 (compare Std. Error = 0.009 for cement in Model 2 versus 0.025 in Model 1), which is a further practical argument, alongside the validation results in Section 4.5, for preferring the simpler five-variable formulation.

Model 3 (four-variable model, C and W excluded)

$$f'c = 127.362 - 118.586(W/C) - 0.064(FA) + 0.001(CA) + 0.067(Age)$$

In this simplified model, the aggregate coefficient became statistically insignificant ($t = 0.108$, $p = 0.914$), while the water-to-cement ratio dominated the standard coefficients (Beta = −0.638), confirming its role as the strongest single predictor when cement and water are not entered separately. The weak overall agreement of Model 3 ($R^2 = 0.555$ vs. 0.627–0.628 for Models 1 and 2) indicates that although the water-to-cement ratio is a strong univariate predictor, some information carried by the cement and water content separately—for example, the total binder available for hydration, regardless of its water ratio-is lost when only the ratio is considered.

Model diagnostics

In all three models, the overall F-statistics were highly statistically significant ($p < 0.001$, Table 4), confirming that each regression explains a statistically significant proportion of the variance in compressive strength. The mean correlations between the predictive variables listed in Table 3b (all $|r|$ values < 0.7) are below the threshold for concern regarding extreme multicollinearity, and the signal pattern of the coefficients in models 1–3 is physically consistent across all three specifications, providing a reasonable confidence community in the stability of the corresponding relationships despite the pooled and multi-source nature of the dataset discussed in Section 5.3.

4.4 Nonlinear (Logarithmic Age) Regression

Replacing the processing age with its natural logarithm (Log_Age) in a complete model with six variables resulted in a slight improvement in calibration fit ($R = 0.806$, $R^2 = 0.650$, adjusted $R^2 = 0.643$, standard error = 8.533 MPa) compared to Model 1. The resulting equation was as follows:

f′c = 63.348 + 0.109(C) − 17.322(W/C) − 0.448(W) − 0.068(FA) + 0.044(CA) + 3.242(LN(Age)) − 0.002(Age)

In this formulation the logarithmic age term (Log_Age) was highly significant (Beta = 0.322, $p < 0.001$) while the untransformed age term became non-significant ($p = 0.875$), confirming that the logarithmic form captures the diminishing-returns pattern of strength gain more effectively than a linear age term. Nevertheless, the improvement in R^2 over Model 1 was modest (0.650 vs 0.628), and, as discussed in Section 4.5, this improvement in calibration fit did not translate into a corresponding improvement on the independent validation set.

4.5 Model Validation

The three linear regression equations (Models 1–3) were each applied to the 50 records reserved for validation, and the predicted strengths were compared with the corresponding measured values. Table 6 summarises the resulting error statistics.

Table 6. *Validation error statistics on the independent hold-out sample (n = 50)*

Model	MAE (MPa)	RMSE (MPa)	MAPE (%)	R (pred. vs actual)
Model 1	11.00	13.31	37.8	0.667
Model 2	10.19	12.69	32.3	0.602
Model 3	10.96	13.12	38.2	0.659

Table 6a. *Sample of predicted vs. measured strength on the validation set – Model 1 and Model 2 (MPa).*

Sample	Measured f′c	Predicted (Model 1)	Predicted (Model 2)
Mix 1	22.00	8.10	14.40
Mix 4	32.00	14.19	20.32
Mix 145	47.99	46.28	43.45
Mix 149	47.16	35.09	33.45
Mix 151	26.84	40.06	40.25
Mix 157	25.97	−0.32	9.58
Mix 170	37.62	36.68	35.82
Mix 176	29.80	29.15	30.69
Mix 178	38.50	39.79	41.03
Mix 313	68.64	51.39	49.36
Mix 360	48.00	50.17	52.35
Mix 365	67.00	53.05	54.18
Mix 380	70.50	42.79	41.77
Mix 382	15.50	4.66	9.15
Mix 400	16.00	24.44	22.94
Mix 421	48.97	50.78	26.82
Mix 425	41.05	33.05	33.99
Mix 431	20.00	33.49	34.64

The sample in Table 6a illustrates the pattern underlying the aggregate error statistics of Table 6: predictions are generally closest to the measured value for mid-range, 28-day, normal-strength mixtures that are well represented in the calibration set, and least accurate for mixtures at the extremes of the sampled ranges (very early ages, very low or very high cement contents, or long-term ages beyond 90 days), where the pooled linear model has comparatively little calibration data to draw on.

All three models show broadly comparable validation performance, with mean absolute percentage errors in the range of 32–38%. Model 2, despite excluding the water-cement ratio, produced marginally lower absolute and percentage errors on the independent sample than Model 1, even though Model 1 had the highest calibration R^2. This is a useful reminder that calibration-set R^2 does not always predict out-of-sample accuracy, particularly for a pooled, multi-source dataset of this kind: the essentially tied calibration fit between Models 1 and 2 (Section 4.3) is reflected in similarly close validation performance, and the small edge shown by Model 2 is consistent with the non-significant W/C coefficient identified in Table 5, since a non-significant predictor can add noise on new data even when it does not visibly harm the calibration fit. Considered together with its simpler five-variable form, Model 2 is put forward as the most practically robust of the three candidates, while the full Model 1 remains a valid and only marginally less accurate alternative. The relatively large error range compared with the very high R^2 values reported in some single-source studies discussed in Section 2 (e.g., [7–10]) reflects the heterogeneity of the pooled 431-record database used here, drawn from multiple independent mixtures, aggregate sources, and testing programmes, which is a more realistic representation of the variability a site engineer would encounter than a single controlled laboratory dataset.

4.6 Sensitivity Analysis

To illustrate the practical effect of the two main predictive variables, calibration equations were used to calculate the predicted force, changing one variable at a time while keeping the remaining variables fixed at representative mean values (water = 180 kg, sand = 700 kg/m³, gravel = 1100 kg/m³, age = 28 days).

Table 7a. *Sensitivity of predicted strength to the water-cement ratio (Model 1, cement = 350 kg/m³, other variables held at mid-range values)*

W/C	0.35	0.45	0.55	0.65
Predicted f'c (MPa)	24.85	22.84	20.83	18.82

Table 7b. *Sensitivity of predicted strength to cement content (Model 2, other variables held at mid-range values)*

Cement (kg/m³)	300	400	500	600
Predicted f'c (MPa)	15.44	27.74	40.04	52.34

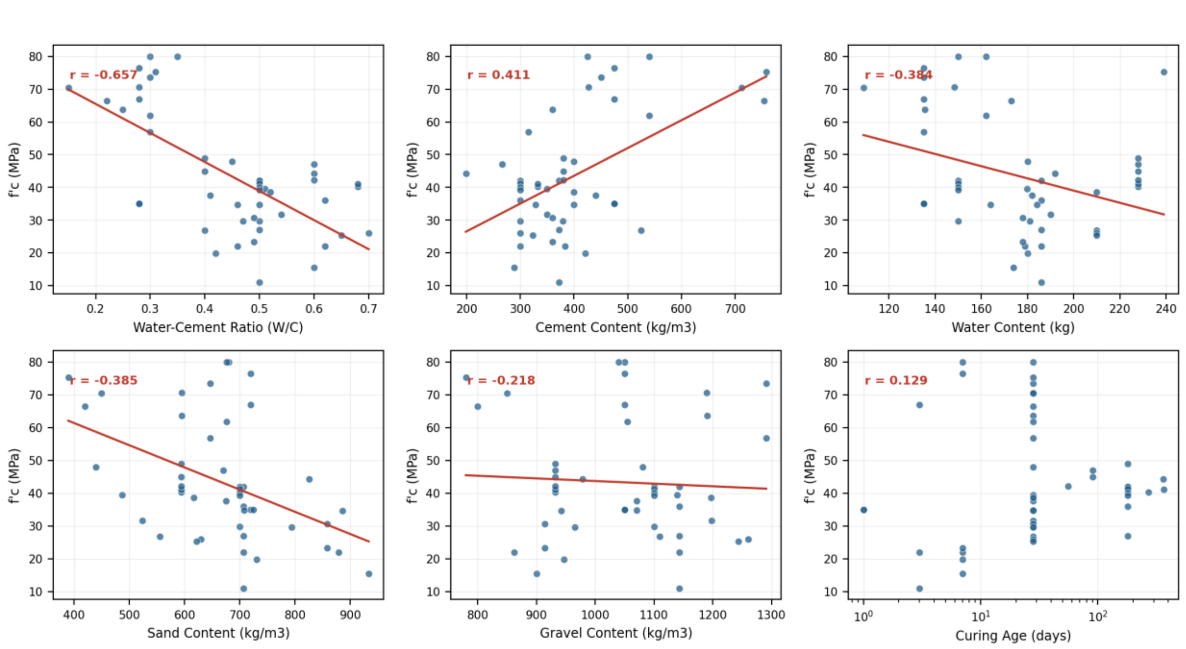
The sensitivity results in Table 7b show a marked increase in predicted resistance with increasing cement content (approximately 12.3 MPa per additional 100 kg/m³ of cement, consistent with the Model 2 coefficient of 0.123), while Table 7a shows a relatively modest predicted change over the same range of water-cement ratio variation when cement and water are considered separately in Model 1 (approximately 2 MPa per 0.10 change in water-cement ratio at constant cement and water content). This directly confirms the earlier finding (Section 4.3) that, once the absolute cement and water content is known, the water-cement ratio itself provides little additional predictive information, although it remains the strongest binary variable associated with resistance (Table 3) when considered in isolation.

4.7 Graphical Illustration of Predictor-Strength Relationships

Further to the tabulated correlation and regression results (Sections 4.2–4.4), Figure 2 illustrates the relationship between the measured compressive strength and each of the six candidate predictive variables individually, using the representative dataset records listed in Tables A1 and A2. Each section of the figure shows the crude dispersion of the individual mixes, as well as a linear trend line (curing life is shown on a logarithmic scale, consistent with the diminishing yield effect discussed in Section 4.4). The Pearson correlation coefficient shown in each section is the value calculated on the complete calibration dataset (n = 381, Table 3), not on the smaller plotted sample, and is cited here for reference.

The water-to-cement ratio (Figure 2a) shows the clearest and most consistent downward trend among all six predictive variables, visually confirming its identification as the strongest bicorrelation variable for strength (r = -0.657). The cement content (Figure 2b) shows a clear upward trend (r = 0.411), while the water, sand, and gravel content (Figures 2c-2e) show weaker downward trends with greater dispersion, reflecting their secondary role and partial linear correlation after accounting for the cement content and water-to-cement ratio (Table 3b). The curing age (Figure 2f) exhibits the most dispersive pattern among the six figures, consistent with its relatively low bidirectional correlation (r = 0.129) in this pooled set of multi-source data; its effect is better observed by the logarithmic transformation used in the nonlinear model in Section 4.4 compared to the untransformed dispersion shown here.

Figure 2. Bivariate relationships between mixture variables and measured compressive strength (representative dataset records, Tables A1-A2; r-values from full calibration set, n = 381)



5. Discussion

The correlation and regression results obtained in this study, in terms of direction and relative value, are consistent with the concrete techniques used and with the previous studies reviewed in Section 2. The water-to-cement ratio emerged as the strongest factor associated with compressive strength (r = −0.657), which is consistent with the results of the studies by Banda and Gupta [13], Neville [15], and Idris and Bello [8], and with the findings regarding the importance of properties by Bansal et al. [19] and Wang et al. [24]. Cement content also showed a consistent positive effect, which is consistent with the results of Namyung et al. [12], Asige et al. [18], and Sevinc [25]. The positive, albeit relatively weak, correlation between curing age (r = 0.129) and concrete strength in the pooled dataset, and its statistical significance improved after logarithmic transformation, reflect the nonlinear relationship between age and strength documented by Darghouli and Hosseinzadeh [4] and Nepatsat and Tangtermesirikol [26].

The near-perfect match in the calibration of models 1 and 2 ($R^2 = 0.628$ vs. 0.627) demonstrates that once cement content and water content are introduced as separate predictive variables, the water-cement ratio adds little explanatory value, as it is ultimately derived mathematically from these two quantities. This has practical implications for engineers using the model: the simpler, five-variable model 2, which does not require separate calculation of the water-cement ratio, can be used with little loss of accuracy, and its slightly lower verification error (Table 6) supports this recommendation. ...The relatively modest R^2 values obtained here (0.55–0.65) and the MAPE validation ratio (32–38%) contrast with the very high R^2 values (0.90 and above) reported by several single-source, small-samples SPSS studies, discussed in Section 2.1 [7–11]. This contrast is useful, not contradictory: those studies typically calibrated and validated their equations on mixtures from a single laboratory or using a narrow ratio system, which reduces unmodeled sources of variance (aggregate source, mixing procedures, and processing environment) and thus tends to produce more accurate matches. The current study deliberately collected 431 records from multiple independent sources, covering cement contents from 270 to 758 kg/m³ and ages from 1 to 180 days. This better represents the variability an engineer might encounter when applying a single general equation to different projects, but it also limits the R^2 value achievable using a linear model. This pattern is consistent with the results of DeRosso et al. [16], which relied on large databases, where their best model achieved a coefficient of determination (R^2) of approximately 0.51 on field data aggregated from multiple sources, and with the results of Young et al. [17], who found that machine learning techniques outperformed classical regression, especially when the underlying database was large and diverse.

The nonlinear logarithm age model offered a slight improvement in calibration (R^2 = 0.650 vs. 0.628) by more accurately tracking the rate of strength gain decline with age than using the linear age term. This aligns with the general finding that concrete strength gain follows a decreasing curve rather than a straight line [4, 26]. However, this improvement did not clearly transfer to the independent validation set, highlighting a common pitfall in regression modeling: the added flexibility of a model can improve its fit to calibration data without necessarily enhancing its generalizability, especially when, as here, the aggregated dataset comprises several different mix families rather than representing a systematic variation of a single mix design.

In practice, the results support the use of SPSS-based multiple linear regression as a screening-level early warning tool, rather than as a replacement for standardized 28-day compliance tests. Accurate prediction within one-third of the measured value is valuable for identifying significantly low-strength batches, guiding mold removal decisions on non-critical elements, or prioritizing batches requiring intensive laboratory monitoring, but it is not accurate enough to replace standard tests for final acceptance. Practitioners intending to apply a regression equation of this type to a specific project will achieve much better accuracy by calibrating the model to data from their own materials and mix designs, following the mix-specific approach demonstrated by Darghouli and Hosseinzadeh [4] for a single dam project, rather than relying on a general, multi-source equation like the one developed here.

5.1 Worked Example of Practical Application

To illustrate how Model 2 could be applied on site, consider a mixture with cement content C = 380 kg/m³, water content W = 190 kg, fine aggregate FA = 700 kg/m³, coarse aggregate CA = 1100 kg/m³, to be evaluated at an age of 7 days. Substituting these values into the Model 2 equation gives:

$$f'c = 63.208 + 0.123(380) - 0.482(190) - 0.086(700) + 0.055(1100) + 0.064(7)$$

$$\boldsymbol{f'c \approx 63.208 + 46.74 - 91.58 - 60.20 + 60.50 + 0.45 \approx 19.1\ MPa}$$

This estimate would allow a site engineer to gauge, within a day of casting, whether the batch is broadly on track relative to a target 28-day strength, and to flag the mixture for closer follow-up if the 7-day estimate appears low relative to the target, well before the standard 28-day compliance test can be completed. As shown by the validation results in Table 6, such an estimate should be treated as indicative, with an expected error on the order of 30% of the measured value, rather than as a substitute for the standard cube or cylinder test.

5.2 Comparison with Previous Studies

Table 7 places the calibration R^2 obtained in the present study alongside representative values reported in the reviewed literature, ordered approximately by dataset size. The comparison illustrates the general trend, discussed above, of decreasing R^2 with increasing dataset size and source heterogeneity.

Table 7. *Indicative comparison of calibration R^2 values across studies of differing dataset scale*

Study	Dataset size (records)	Method	R^2 (calibration)
Hussain et al. [7]	56	SPSS – MLR	0.949
Idris & Bello [8]	– (narrow W/C range)	SPSS – MLR	High (not quantified)
Bansal et al. [19]	1,030 (UCI)	Optimised ML	0.940
Hematibahar & Kharun [21]	>45	Ridge / Polynomial	0.91–0.93
Present study – Model 1	381	SPSS – MLR	0.628
Present study – nonlinear (log-age)	381	SPSS – nonlinear	0.650
DeRousseau et al. [16]	1,681 (field) + 1,000+ (lab)	Regression / Polynomial	≈0.51 (field)

The present study's calibration R^2 (0.63–0.65) sits between the very high values reported by small, single-source SPSS studies and the more moderate value reported by DeRousseau et al. [16] for a large, pooled field database, which is consistent with the intermediate scale (381 calibration records from multiple sources) of the dataset compiled here.

5.3 Limitations of the Study

1. The dataset was compiled from multiple previously published studies rather than a single controlled experimental programme; differences in cement type, aggregate source, testing procedure, and curing environment between the original sources are not captured by the six recorded variables and are likely to contribute to the unexplained variance ($R^2 \approx 0.63$) in Models 1 and 2.
2. The models are restricted to normal-weight concrete without supplementary cementitious materials, admixtures, or special curing regimes; extrapolation of the regression equations beyond the sampled ranges of cement content (270–758 kg/m³), water-cement ratio (0.15–0.70), and curing age (1–180 days) is not recommended.
3. Although the validation set of 50 records is independent of the calibration set, it was compiled from the same literature sources and therefore may not fully represent the conditions of any specific project or region.
4. As a linear method, multiple linear regression can only detect the effects of interactions between predictive variables (e.g., between cement content and curing age) by explicitly adding these interaction terms, which is beyond the scope of this study.

5.4 Implications for Standards and Practice

International standards such as ACI 318, ASTM C39, and EN 206 base concrete acceptance on the standard 28-day compressive strength test, with early-age testing (commonly at 7 days) used only as an informal indicator of expected 28-day performance rather than as a basis for formal acceptance. The regression models developed in this study are intended to complement, not replace, this standards-based acceptance framework: they provide a rapid, low-cost, and standards-compatible early indicator that can be computed from routinely recorded batch data (cement, water, aggregate proportions, and age) without additional testing, and can therefore support proactive quality management – for example, flagging a batch for closer laboratory follow-up, or triggering a mix-design review – well before the formal 28-day compliance result becomes available. Because the prediction error reported in Section 4.5 (MAPE of 32–38%) is too large for the regression equations to be used as a substitute for standard testing in acceptance or rejection decisions, any such use should be clearly distinguished, in project quality-management documentation, from the formal acceptance testing required by the applicable standard.

6. Conclusions

Based on the statistical analysis of 431 concrete mix records using SPSS software, the following conclusions were reached:

1. The water-cement ratio and cement content are the two main factors affecting the compressive strength of concrete within the pooled dataset. They exhibited the highest Pearson correlation coefficients ($r = -0.657$ and $r = 0.411$, respectively) among the six variables studied, consistent with established concrete techniques.

2. Three multiple linear regression models were developed. The full six-variable model (Model 1) and the five-variable model excluding the water-cement ratio (Model 2) achieved high agreement in calibration accuracy ($R^2 \approx 0.628$ and 0.627), indicating that the water-cement ratio does not provide a significant independent explanatory value when the cement and water content are entered separately.

3. The reduced model with four variables excluding cement and water content (Model 3) produced a significantly weaker fit ($R^2 = 0.555$), confirming that cement and water content together carry more predictive information than the water-to-cement ratio alone.

4. A logarithmic transformation of curing age improved the calibration fit modestly ($R^2 = 0.650$) and rendered the age effect statistically more significant, confirming the expected nonlinear (decelerating) nature of strength gain with time; however, this improvement did not clearly carry over to the independent validation sample.

5. Independent validation on 50 hold-out records showed mean absolute percentage errors of 32–38% across the three linear models, with the five-variable Model 2 showing marginally the best validation performance despite its simpler form, indicating that calibration R^2 alone is not a reliable guide to out-of-sample accuracy for a pooled, multi-source dataset of this kind.

6. SPSS-based multiple linear regression is a practical, transparent, and low-cost tool that site and quality-control engineers can use for early, approximate estimation of concrete compressive strength, though its current accuracy is best suited to screening and early-warning purposes rather than to final compliance decisions.

Recommendations

The following recommendations follow from the limitations identified in Section 5.3 and are intended to guide both the immediate practical use of the present models and future extensions of this line of research.

1. Expand the database with additional, well-documented mixtures, and where possible calibrate project-specific versions of the equations using data from the materials and mix designs actually used on a given site, following the localised approach shown to improve accuracy in dam-construction quality control.

2. Screen and treat outliers carefully before regression modelling, since pooled multi-source datasets are particularly prone to inconsistent or mislabelled records.

3. Extend future models to include supplementary cementitious materials, chemical admixtures, and curing-condition variables, which were outside the scope of the present six-variable dataset but are known to influence strength.
4. Validate any generic regression equation, including those developed here, against independent data from the specific materials and conditions before it is used for engineering decisions.
5. Explore hybrid approaches that combine the transparency of SPSS regression with the higher accuracy of machine-learning techniques for large, heterogeneous datasets, consistent with recent comparative findings in the literature.

Author Contributions

D.H.A. and E.S.K. carried out data collection, SPSS analysis, and drafting of the original thesis on which this paper is based; A.A. supervised the research, verified the statistical methodology, and prepared the present manuscript for journal submission, including the additional validation-error analysis, literature synthesis, and discussion presented in Sections 4.5, 5.1, and 5.3. All authors reviewed and approved the final manuscript.

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Data Availability Statement

The compiled dataset supporting the findings of this study is available from the corresponding author upon reasonable request. A representative subset is provided in Appendix A.

Conflicts of Interest

The authors declare no conflict of interest.

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Nomenclature

Symbol	Description
f'c	Concrete compressive strength (MPa)
C	Cement content (kg/m³)
W	Water content (kg)
W/C	Water-cement ratio
FA	Fine aggregate (sand) content (kg/m³)
CA	Coarse aggregate (gravel) content (kg/m³)
Age	Curing age (days)
β0	Regression intercept
β1…βn	Regression coefficients
R, R^2	Correlation coefficient and coefficient of determination
MAE, RMSE, MAPE	Mean absolute error, root-mean-square error, mean absolute percentage error
MLR	Multiple linear regression
SPSS	Statistical Package for the Social Sciences

Highlights

- A 431-record, multi-source concrete database was compiled and used to build fully transparent SPSS regression equations for compressive strength prediction.
- Cement content and the water-cement ratio were confirmed as the dominant predictors, with a strong negative correlation for W/C ($r = -0.657$).
- A five-variable model excluding the water-cement ratio matched the full six-variable model in calibration fit and gave marginally better independent validation performance.

- Converting age to a logarithmic scale improved calibration accuracy but did not significantly improve the accuracy of out-of-sample model validation.
- Independent validation showed an average absolute relative error of 32%–38%, making these models an early screening tool rather than a replacement for standard 28-day testing.

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Compliance with ethical standards

Disclosure of conflict of interest

The authors declare that they have no conflict of interest.