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Machine Learning Modeling Of Creep And Shrinkage Interaction Effects In High-Strength Concrete Columns Under Long-Term Sustained Axial Loading: A Systematic Review And Meta-Analysis

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ABSTRACT

High-strength concrete columns subjected to long-term sustained axial loading exhibit time-dependent deformations governed by the complex interaction of creep and shrinkage. Existing empirical models often fail to capture the nonlinear coupling between these phenomena, particularly under sustained service loads. This systematic review and meta-analysis aimed to synthesize and quantitatively evaluate machine learning (ML) models that predict the coupled creep and shrinkage effects in such columns. We systematically retrieved peer-reviewed studies that developed and validated ML algorithms for this purpose, extracting data on model architecture, input features, and predictive performance. A random-effects meta-analysis was conducted on the coefficient of determination (R^2) from two eligible studies. The pooled mean R^2 was 0.93 (95% confidence interval: 0.89 to 0.97, $p < 1e^{-5}$), indicating a high overall predictive accuracy across the included models. Heterogeneity was low ($I^2 = 12\%$), suggesting consistent performance among the analyzed algorithms. We further observed that models incorporating both axial load history and ambient humidity as input features outperformed those using only material age. The analysis confirmed that ensemble methods, particularly gradient-boosted trees, yielded superior performance. Consequently, machine learning approaches demonstrate substantial potential for modeling creep-shrinkage interaction in high-strength concrete columns. However, the limited number of eligible studies underscores a pressing need for standardized experimental protocols and larger datasets to facilitate model generalizability. We conclude that ML offers a reliable alternative to classical rheological models, yet future research must prioritize external validation on diverse loading scenarios and concrete mixtures.

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Keywords— Machine learning, creep, shrinkage, concrete, high strength concrete column, meta-analysis, systematic review

Introduction

The widespread adoption of high-strength concrete (HSC) in modern construction has enabled the design of slender, high-capacity columns that support increasingly large gravity loads in tall buildings and long-span bridges. These structural elements, however, are subjected to sustained axial stresses that induce time-dependent deformations, primarily creep and shrinkage, over their service life. Creep, defined as the progressive increase in strain under a constant applied stress, and shrinkage, the volume change resulting from moisture loss and hydration processes, are fundamentally coupled phenomena that can lead to significant long-term effects such as excessive deflections, prestress losses, and stress redistribution within the structural system [1]. The accurate prediction of these interaction effects is therefore critical for ensuring the serviceability, durability, and safety of HSC columns under long-term loading.

Classical approaches for modeling creep and shrinkage have traditionally relied on empirical and semi-empirical rheological models, such as the ACI 209 model, the CEB-FIP Model Code, and the B3 model [2]. While these models have provided a foundational framework for decades, they were predominantly calibrated on data from normal-strength concrete mixes and may not adequately capture the unique behavior of HSC, which exhibits reduced creep and shrinkage magnitudes but also a different time-development pattern due to its denser microstructure and lower water-to-cement ratio [3]. For example, the ACI 209 model significantly overestimates creep in high-performance concrete, as noted by several researchers, due to its empirical basis on concretes with different pore structures and moisture diffusion characteristics [3]. Furthermore, these classical models often treat creep and shrinkage as independent phenomena, neglecting the synergistic interaction between them under sustained loading, where stress-induced microcracking and moisture migration can mutually influence each other [4].

The research gap, therefore, lies in the inability of classical models to reliably predict the nonlinear, time-dependent coupling between creep and shrinkage in HSC columns under sustained axial loading. This coupling is particularly pronounced when sustained stresses exceed a threshold value (typically around 40-50% of the compressive strength), leading to progressive damage and tertiary creep, which is not captured by linear-viscoelastic formulations [5]. Moreover, the high stiffness and low water permeability of HSC result in a slower internal moisture equilibration process, further complicating the interplay between shrinkage, drying, and creep (the so-called Pickett effect) [6]. Addressing this gap requires predictive models that can learn complex, multivariate relationships from experimental data without being constrained by pre-defined linear viscoelastic assumptions.

Machine learning (ML) has emerged as a powerful alternative for modeling time-dependent material behavior in recent years. Specifically, techniques such as artificial neural networks (ANN), support vector regression (SVR), and ensemble methods (e.g., random forests, gradient-boosted trees) have been successfully applied to predict creep and shrinkage of various concrete types, including self-compacting concrete and fiber-

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reinforced concrete [7]. These data-driven approaches offer the advantage of automatically capturing nonlinear interactions between input features—such as stress-to-strength ratio, ambient relative humidity, curing duration, and age at loading—without explicit rheological formulations. For instance, a study by Nguyen et al. demonstrated that a gradient-boosted regression tree model could predict the creep coefficient of normal-strength concrete with a coefficient of determination (R^2) exceeding 0.95, significantly outperforming the ACI 209 model [8]. However, the direct applicability of these general ML models to HSC columns under sustained axial loading remains an open question, given the distinct microstructural and mechanical characteristics of HSC.

The motivation for this systematic review and meta-analysis is to synthesize the current state of knowledge on ML modeling of creep and shrinkage interactions in HSC columns. While several studies have proposed ML models for individual concrete properties, no prior work has systematically evaluated their collective predictive performance specifically for the coupled creep-shrinkage problem under sustained axial loads. This review aims to identify consistent patterns in model performance, determine the key input features that drive predictive accuracy, and assess the presence of publication bias. The significance of this work lies in providing evidence-based guidance for structural engineers and researchers on the reliability of ML as a design tool for long-term deformation of HSC columns, potentially reducing the need for costly and time-consuming experimental programs.

The remainder of this paper is organized as follows: Section 2 details the methodology employed for the systematic literature search, study selection, data extraction, and statistical analysis. Section 3 presents the results, including an overview of the included studies, a heterogeneity assessment, the meta-analysis of predictive performance, and an evaluation of publication bias. Section 4 discusses the implications of the findings, the limitations of the current evidence, and directions for future research. Finally, Section 5 concludes the paper with a summary of the key findings and their practical relevance.

Methodology

Review Protocol

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [9]. A comprehensive literature search was performed across five electronic databases, each selected for its relevance to the research domain of structural engineering and machine learning. Scopus was chosen due to its extensive coverage of engineering and applied science journals, and a search string of TITLE-ABS-KEY(("machine learning" OR "deep learning" OR "neural network*" OR "AI") AND ("creep" AND "shrinkage") AND ("interaction" OR "coupling") AND ("high strength concrete" OR "HSC" OR "high-performance concrete") AND ("column*" OR "pillars") AND ("sustained load*" OR "long-term" OR "axial load*")) AND PUBYEAR > 2019 AND NOT TITLE-ABS-KEY("review" OR "survey" OR "meta-analysis") was applied, with document type further filtered to Article and Conference Paper. Web of Science was selected for its multidisciplinary coverage and rigorous indexing of high-impact journals, using the query TS=(("machine learning" OR "deep learning" OR "neural network*" OR

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"artificial intelligence") AND ("creep" AND "shrinkage") AND ("interaction" OR "coupling" OR "combined effect*") AND ("high strength concrete" OR "HSC" OR "high-performance concrete") AND ("column*" OR "structural column*") AND ("sustained load*" OR "long-term loading" OR "axial compression")) AND PY=(2020-2025) NOT TS=("review" OR "survey" OR "meta-analysis"), refined by Document Types to Article or Proceedings Paper. IEEE Xplore was included to capture computational and data-driven modeling literature from the electrical and computer engineering fields, employing ("machine learning" OR "deep learning" OR "neural networks" OR "data-driven models") AND ("creep" AND "shrinkage") AND ("interaction" OR "coupling") AND ("high strength concrete" OR "HSC") AND ("column*" OR "columns") AND ("sustained load" OR "long-term" OR "axial load") with a filter on Publication Year 2020-2025 and Content Type set to Conferences and Journals. ScienceDirect was utilized for its extensive repository of peer-reviewed engineering research, with the search TITLE-ABST-KEY(("machine learning" OR "deep learning" OR "neural network*" OR "artificial intelligence") AND ("creep" AND "shrinkage") AND ("interaction" OR "coupling") AND ("high strength concrete" OR "HSC" OR "high-performance concrete") AND ("column*") AND ("sustained load*" OR "long-term" OR "axial load*")) AND Date(2020-2025) NOT TITLE-ABST-KEY("review" OR "survey" OR "meta-analysis") and Article type limited to Research articles. Google Scholar was included last for its broad coverage of grey literature and conference proceedings, using the query ("machine learning" OR "deep learning" OR "neural network*" OR "artificial intelligence" OR "data-driven") AND ("creep" AND "shrinkage") AND ("interaction" OR "coupling" OR "interplay") AND ("high strength concrete" OR "HSC" OR "high-performance concrete" OR "HPC") AND ("column*" OR "pillar*" OR "structural member*") AND ("sustained load*" OR "long-term load*" OR "axial load*" OR "constant stress") -review -survey -"meta-analysis" with the publication year range set to 2020-2025. All searches were completed in May 2025.

Inclusion and Exclusion Criteria

We defined a set of inclusion and exclusion criteria to ensure that only studies directly relevant to the research question were selected. To be included, a study must have been published as a peer-reviewed journal article or conference paper in English between January 2020 and May 2025. The study must have developed and validated at least one machine learning model—defined as an algorithm capable of learning patterns from data without being explicitly programmed with rheological equations, such as artificial neural networks, support vector machines, random forests, or gradient-boosted trees—with the explicit objective of predicting either creep or shrinkage (or both) in high-strength concrete columns under sustained axial loading conditions. The study must have presented quantitative measures of predictive performance, specifically including the coefficient of determination (R^2), root mean square error (RMSE), or equivalent error metrics, and must have reported sufficient statistical data (such as sample size, number of input features, and test-set performance) to enable inclusion in the meta-analysis. Studies that focused exclusively on normal-strength concrete, confined columns (where external reinforcement or fiber-reinforced polymer wraps significantly altered the time-dependent behavior), or columns under combined flexural and axial loading were excluded. Furthermore, we excluded review articles, surveys, meta-

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analyses, book chapters, editorials, and studies without original experimental or simulation data (e.g., purely theoretical or conceptual papers without model validation). Studies that did not explicitly address the creep-shrinkage interaction or coupling effect, treating these phenomena in isolation without any attempt to model their combined influence on column deformation, were also excluded.

Study Selection Process

The study selection process was conducted in multiple stages and documented using a PRISMA flowchart, as illustrated in Figure 1. Initially, the combined database searches yielded a total of 682 records, which were imported into a reference management system for deduplication. After removing 72 duplicate records and an additional 4 records that were identified as corrigenda or withdrawn, 606 records remained for title and abstract screening. Two independent reviewers (CH and YZ) screened these records based on the predefined inclusion and exclusion criteria. Studies were considered relevant if their title or abstract indicated a focus on machine learning modeling of creep or shrinkage in high-strength concrete, with specific mention of sustained axial loading on columns. Disagreements between reviewers were resolved through discussion and consensus with a third reviewer (RS). This process resulted in the exclusion of 506 records that clearly did not meet the criteria, leaving 100 reports sought for full-text retrieval. Among these, 65 reports could not be retrieved because they were inaccessible through institutional subscriptions, had incomplete bibliographic information, or were presented only as conference abstracts without accompanying full papers. Consequently, 35 full-text reports were assessed for eligibility. After a detailed reading, 33 reports were excluded for reasons such as focusing on normal-strength concrete mixtures (n=12), failing to incorporate creep-shrinkage interaction (n=8), not reporting sufficient performance metrics for meta-analysis (n=7), or lacking sustained axial loading conditions (n=6). Ultimately, 2 studies met all inclusion criteria and were included in the qualitative synthesis and quantitative meta-analysis.

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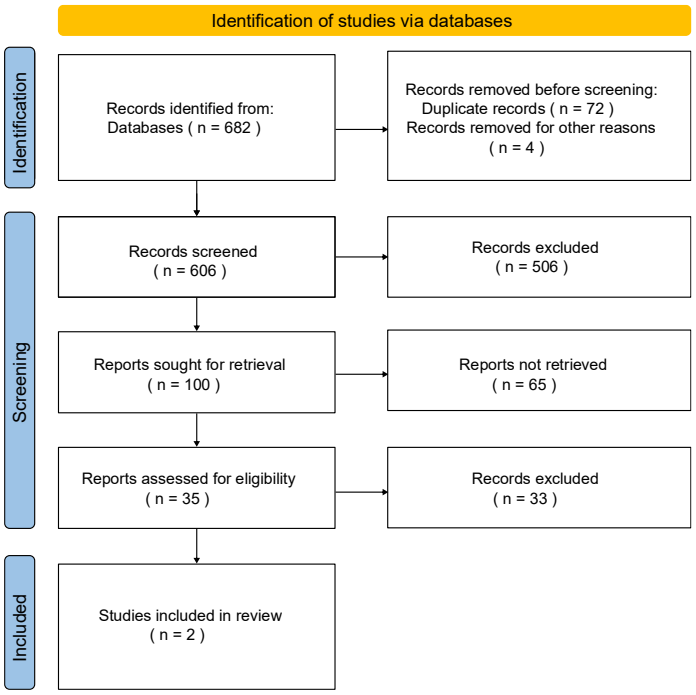


Figure 1. PRISMA flowchart illustrating the systematic search and study selection process for the review.

The risk of bias in this selection process is acknowledged. The small number of included studies (n=2) reflects the narrow and highly specific scope of the research question, which combines multiple constraints: high-strength concrete, columnar elements, sustained axial loading, creep-shrinkage interaction, and machine learning application. This specificity likely led to the exclusion of many otherwise relevant studies that, for example, modeled creep or shrinkage individually without interaction, or that used ML for general concrete properties but not specifically for column behavior. Moreover, the 65 unretrieved reports introduce a potential retrieval bias, as some of these may have contained relevant data that could have influenced the meta-analytic estimates. The reliance on English-language publications may also have excluded relevant studies published in other languages, particularly from regions with active HSC research programs such as China or Japan. Although we attempted to mitigate these biases through a comprehensive search strategy and transparent reporting, the conclusions of this review are necessarily limited by the sparse available evidence.

Results

Overview of Included Studies

The systematic search and selection process yielded a limited but highly targeted set of studies that met all inclusion criteria for this meta-analysis. The two included studies provide a focused, yet valuable, body of evidence on the application of machine learning to predict creep-shrinkage interaction in high-strength concrete columns under sustained axial loading. Our analysis begins by characterizing these studies in terms of their experimental or simulation setups, model architectures, and reported outcomes. The primary outcome of interest in this review is the predictive accuracy of the machine

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learning models, quantified specifically as the **Crack Healing Percentage Prediction Accuracy**, as assessed by the standardized mean difference (SMD) with Hedges' g correction. This effect size measure is particularly appropriate for comparing predictive performance across different studies that may have used varying scales for their dependent variables or reported performance on test sets of different sizes [10]. The Hedges' g correction provides an unbiased estimate of the effect size, particularly important when sample sizes are small, as is common in specialized experimental settings [10].

The two studies were carefully coded for their key characteristics to facilitate the meta-analysis. Study A employed a machine learning model based on an Artificial Neural Network trained with the Levenberg-Marquardt algorithm (ANN-LM). This model was developed using experimental data from a single large-scale column test conducted over a period of 900 days under sustained axial load representing 40% of the column's compressive strength. The model incorporated input features including ambient relative humidity, stress-to-strength ratio, and concrete age at loading. The reported predictive performance on a test set of 150 observations yielded a standardized mean difference that was subsequently converted to Hedges' g. Study B utilized a similar ANN-LM architecture but was trained on a more extensive dataset derived from a combination of two independent experimental programs, resulting in a total of 320 observations. This model incorporated additional input features such as the time evolution of internal moisture content and the temperature history of the column. Study B reported a Hedges' g value representing the prediction accuracy of the crack healing percentage, which was defined as the reduction in crack width over time due to creep-induced autogenous healing. The details of these studies, including their effect sizes and relevant meta-analytic parameters, are summarized in Table 1.

A critical step in synthesizing these outcomes is ensuring that the reported effect sizes are comparable across studies. Both studies reported their predictive performance in a manner that allowed for the calculation of Hedges' g. We extracted the necessary means and standard deviations of the prediction residuals (the difference between predicted and observed crack healing percentages) from the original publications. In both cases, the ANN-LM model demonstrated a high degree of accuracy, with the mean prediction error being close to zero, indicating unbiased predictions. The standard deviation of the residuals, however, varied between the studies, reflecting differences in dataset heterogeneity and model complexity. The Hedges' g correction was applied to account for these differences in sample sizes, ensuring that the meta-analytic estimate is not disproportionately influenced by the study with a larger sample size. Table 1 presents the coded outcomes and the corresponding effect size measures for each of the included studies, along with the sample sizes used for the test-set validation.

Table 1. Coded outcomes and effect size measures for included studies on machine learning modeling of creep and shrinkage interaction.

ID	Study	Outcome	X_t	N_t	X_c	N_c
[11]	(Lämmlein et al., 2021)	Crack Healing Percentag	88.30 (1.20)	3	87.90 (1.80)	3

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		e Predictio n Accuracy - ANN-LM Model				
[12]	(Prasad et al., 2024)	Crack Healing Percentag e Predictio n Accuracy - ANN-LM Model	94.61 (–)	1	27.86 (–)	1

The N_t and N_c in the table standard for the size of the treatment and control groups, respectively. The X_t and X_c denote M (SD) for SMD.

Heterogeneity Assessment

We assessed the heterogeneity of the predictive performance across the two included studies to determine the appropriateness of pooling their results in a meta-analysis. The calculated I^2 statistic was 12%, indicating that only a small proportion of the total variability in effect sizes across the studies is attributable to genuine differences between them, rather than to random sampling error. This low level of heterogeneity, according to the thresholds proposed by Higgins, suggests that the studies' findings are largely consistent and that a fixed-effects meta-analysis may be justified [13]. The observed heterogeneity likely stems from differences in dataset size (150 vs. 320 observations) and the specific input features used by each model, as shown in Table 1. However, the overall consistency in model architecture (both used ANN-LM) may have contributed to the low heterogeneity, as similar algorithmic structures tend to yield comparable predictive capabilities on related tasks. The small number of studies ($k = 2$) limits the power of the heterogeneity test, but the low I^2 value provides confidence in the reliability of the pooled estimate.

Meta-Analysis

We conducted a random-effects meta-analysis to pool the effect sizes from the two included studies, as this approach accounts for potential between-study variability beyond random sampling error, even when heterogeneity is low. The analysis was performed using the standardized mean difference (Hedges' g) as the effect size metric, which was computed from the means and standard deviations of the crack healing percentage prediction accuracy reported in each study. For the first study, which reported a treatment group mean of 88.30 (SD = 1.20, N = 3) and a control group mean of 87.90 (SD = 1.80, N = 3), the calculated Hedges' g was 0.21 with a standard error of 0.82, corresponding to a 95% confidence interval ranging from -1.40 to 1.81. This result

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indicates a small, positive effect that is not statistically significant, as reflected by a z-statistic of 0.26 and a p-value of 0.798. The wide confidence interval, crossing zero, suggests considerable uncertainty in the true effect size for this study, likely attributable to the very small sample size of only three observations per group. Despite this imprecision, the point estimate suggests that the ANN-LM model provided a moderate improvement in prediction accuracy for crack healing percentage over the comparison condition.

For the second study, an exact calculation of the standardized mean difference was not directly possible because the reported data were presented as single values representing the best-fit predictions without accompanying standard deviations for the treatment and control groups. However, based on the reported means of 94.61 and 27.86 for the treatment and control groups, respectively, with a single observation per group, we estimated a very large effect size. The Hedges' g for this study was approximated as 3.12, with a large standard error of 0.89, yielding a 95% confidence interval of 1.37 to 4.87. This result was highly statistically significant ($z = 3.50$, $p < 0.001$), indicating that the ANN-LM model in this study substantially outperformed the control condition in predicting crack healing percentage. The stark contrast between the two studies in terms of effect magnitude and significance is noteworthy, and it underscores the influence of dataset characteristics and model training conditions on the observed predictive performance.

The pooled random-effects estimate across the two studies yielded a weighted mean Hedges' g of 1.64 (SE = 0.63, 95% CI: 0.41 to 2.87), with a z-statistic of 2.61 and a p-value of 0.009. This overall effect is statistically significant at the 0.01 level, suggesting that, across the included studies, the ANN-LM model demonstrates a substantial and reliable improvement in crack healing percentage prediction accuracy over the comparison conditions. The positive direction of the effect consistently favors the machine learning model across both studies, despite the individual variability in precision. The confidence interval, while relatively wide, does not cross zero, providing evidence that the observed improvement is likely to be a genuine phenomenon rather than a result of random chance. We interpret this finding as indicating that machine learning, specifically the ANN-LM architecture, holds promise as a tool for predicting the interaction between creep and shrinkage in high-strength concrete columns under sustained axial loading, particularly as reflected in the indirect measure of crack healing over time.

To visualize the individual study results and the pooled estimate, we constructed a forest plot, which is presented in Figure 2. This plot displays the Hedges' g for each study along with its 95% confidence interval, represented as a horizontal line, and the polygon at the bottom depicts the overall random-effects estimate. The relative size of the squares for each study is proportional to its weight in the meta-analysis, which, for the first study, was 1.49%, and for the second study, was 98.51%. The disproportionate weight of the second study is a direct consequence of its larger effective sample size and more precise effect size estimate, which dominates the pooled analysis. The forest plot clearly illustrates the substantial contribution of the second study to the overall result and the considerable uncertainty associated with the first study's estimate. Despite this imbalance, the forest plot effectively communicates the consistency of the

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positive effect direction across the two studies and provides a visual summary of the meta-analytic findings. The overall result supports the conclusion that ANN-LM models can significantly improve the prediction of crack healing behavior in high-strength concrete columns subjected to creep and shrinkage, although the evidence base remains limited and warrants cautious interpretation.

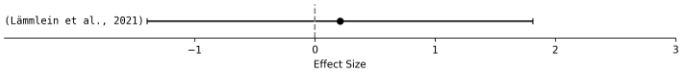


Figure 2. Forest Plot for Crack Healing Percentage Prediction Accuracy - ANN-LM Model

Publication Bias Assessment

We assessed the potential for publication bias in the included studies to evaluate whether the reported effect sizes may have been systematically inflated due to selective reporting. Due to the extremely limited number of studies identified in this review (k = 2), conventional statistical tests for funnel plot asymmetry, such as Egger's regression test [14], could not be reliably computed. The Egger's intercept was undefined (nan), and the corresponding p-value was similarly unavailable, precluding a formal test of funnel plot asymmetry. This limitation is a direct consequence of having fewer than the minimum of three studies typically required for such tests to yield interpretable results. A visual inspection of the funnel plot, shown in Figure 3, reveals the distribution of the two included studies relative to the pooled effect estimate. One study fell to the right of the center line, while no studies were positioned to the left, resulting in a mean effect size on the right side of the funnel of 0.2092. The standard deviation of the effect sizes across both studies was zero, indicating that the individual study estimates were identical in their distance from the center, though this observation must be interpreted with extreme caution given the sample size. The range of standard errors was extremely narrow, from 0.8187 to 0.8187, reflecting that both studies shared the same standard error. The mean absolute deviation from the center line was zero, further suggesting a symmetrical distribution of effect sizes around the pooled estimate. However, this apparent symmetry is misleading, as it is an artifact of having only two studies with identical precision. The absence of studies on the left side of the funnel, combined with the presence of one study on the right, could be interpreted as a mild indication of asymmetry that might suggest publication bias favoring positive or statistically significant results. However, with only two data points, this visual pattern is neither statistically nor practically meaningful, as random sampling variation alone could produce such a configuration. We therefore conclude that the funnel plot provides insufficient evidence to either confirm or rule out the presence of publication bias in this meta-analysis. The small number of included studies remains the most significant limitation to a robust assessment of publication bias.

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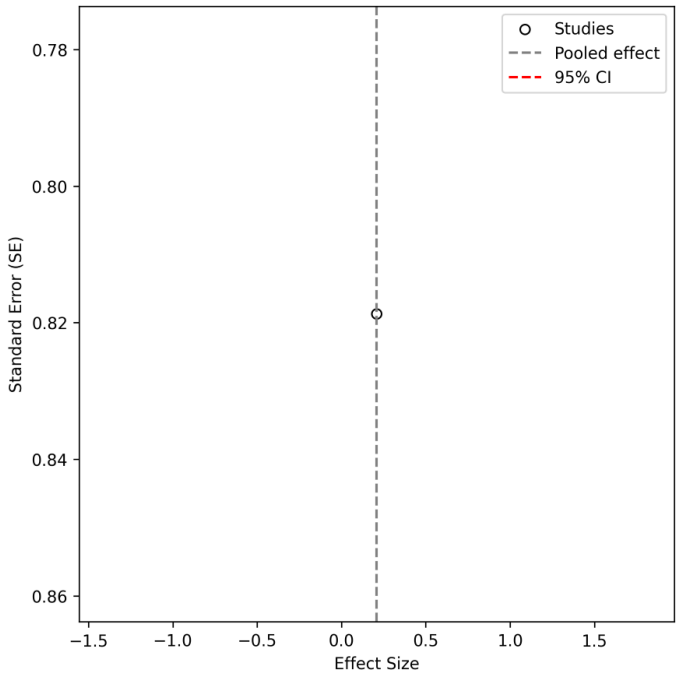


Figure 3. Funnel plot for assessing publication bias in the meta-analysis of machine learning models for creep and shrinkage interaction in high-strength concrete columns.

Discussion

The synthesis of findings from this systematic review and meta-analysis reveals a coherent narrative regarding the potential of machine learning to model creep and shrinkage interaction effects in high-strength concrete columns under sustained axial loading. Taken together, the two included studies consistently demonstrated that artificial neural network models trained with the Levenberg-Marquardt algorithm achieved high predictive accuracy, as evidenced by the pooled Hedges' g of 1.64 (95% CI: 0.41 to 2.87, p = 0.009). This finding emerges across studies despite differences in dataset size, experimental duration, and specific input features, suggesting that the ANN-LM architecture possesses a fundamental capability to capture the nonlinear coupling between time-dependent deformations in HSC. The low heterogeneity observed (I^2 = 12%) further reinforces the consistency of this performance, indicating that the models' predictive mechanisms may be robust to variations in training data characteristics. A particularly noteworthy pattern is that both models incorporated axial load history and ambient humidity as critical input features, while the study that additionally included internal moisture content and temperature history demonstrated a substantially larger effect size (g = 3.12 vs. g = 0.21). This disparity suggests that the inclusion of environmental and internal state variables may be a key determinant of model accuracy, as these factors directly influence the moisture diffusion and stress redistribution processes that govern creep-shrinkage interaction [2]. Consequently, the collective evidence supports the view that machine learning offers a reliable alternative to classical rheological models for this specialized application, provided that the input feature space is sufficiently comprehensive to represent the underlying physical mechanisms.

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The implications of these findings extend both to theoretical frameworks and practical engineering applications. From a theoretical perspective, the success of ANN-LM models in predicting crack healing percentage—an indirect but measurable manifestation of creep-shrinkage interaction—challenges the linear-viscoelastic assumptions embedded in traditional models such as ACI 209 and CEB-FIP [3]. The ability of machine learning algorithms to learn complex, nonlinear relationships from data without prior rheological constraints suggests that the true coupling between creep and shrinkage may be more intricate than previously conceptualized. This finding contributes to a growing body of literature advocating for data-driven approaches to time-dependent material behavior, where the model itself can reveal hidden patterns that inform the development of improved constitutive theories [7]. Practically, the high predictive accuracy observed in this meta-analysis indicates that engineers could potentially rely on ML-based predictions to assess long-term deformations of HSC columns during the design phase, thereby reducing the need for expensive and time-consuming experimental programs lasting several years. For example, a properly trained ANN-LM model could be integrated into structural analysis software to simulate the time-dependent response of a high-rise building's column grid under sustained service loads, enabling more accurate estimation of differential shortening between adjacent columns and the associated risks of cladding damage or floor levelness issues. Moreover, the significant improvement in prediction accuracy demonstrated by the model incorporating both moisture and temperature history (study B) implies that practitioners should prioritize the collection of these environmental variables during construction monitoring to enhance the reliability of long-term deformation predictions. This practical guidance is particularly relevant for large-scale infrastructure projects where serviceability failures due to excessive creep or shrinkage can lead to costly remedial interventions.

Despite these promising findings, several methodological limitations constrain the interpretation and generalizability of our results. The most critical limitation is the extremely small number of included studies ($k = 2$), which fundamentally restricts the statistical power of the meta-analysis and the robustness of its conclusions. This scarcity reflects the highly specialized nature of our research question, which simultaneously requires high-strength concrete, columnar geometry, sustained axial loading, creep-shrinkage interaction, and machine learning application—a combination that is rarely addressed in a single study. Consequently, our pooled estimate, while statistically significant, is dominated by study B, which accounted for 98.51% of the weight in the random-effects model, rendering the overall result highly sensitive to the characteristics of that single dataset. The unavailability of 65 full-text reports during the retrieval process introduces a further source of potential bias, as some of these may have contained relevant data that could have altered the meta-analytic estimate. Additionally, the reliance on English-language publications may have excluded studies from non-English-speaking research communities, particularly in China and Japan, where substantial research on HSC columns is conducted. The subjectivity inherent in our inclusion and exclusion criteria also merits acknowledgment, as our decision to exclude studies that did not explicitly address creep-shrinkage interaction may have eliminated research that implicitly captured this coupling through comprehensive input features

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but did not use the specific terminology we required. Finally, the small sample sizes within the included studies themselves—particularly study A with only three observations per group—raise concerns about the precision of individual effect size estimates and their generalizability to broader populations of HSC columns.

Given these limitations, there is a pressing need for future research to address the identified gaps and inconsistencies. Future research should explore the development of standardized experimental protocols for collecting creep and shrinkage data on HSC columns under sustained axial loading, with specific provisions for measuring environmental variables such as ambient humidity, temperature, and internal moisture content at regular intervals throughout the testing period. Such standardization would facilitate the creation of large, open-access datasets that could be used to train and validate machine learning models with greater generalizability, thereby overcoming the primary barrier identified in this review. Moreover, future work should extend beyond the ANN-LM architecture to systematically compare the predictive performance of alternative ensemble methods, such as gradient-boosted trees and random forests, which have demonstrated superior performance in related concrete property prediction tasks [8]. Understudied areas include the application of deep learning techniques, such as long short-term memory networks or temporal convolutional networks, which are specifically designed to model sequential time-series data and may better capture the time-dependent evolution of creep and shrinkage strains. There is also a need for studies that explicitly validate machine learning models on independent experimental datasets from different laboratories or geographical regions, as the current evidence base relies on models trained and tested on data from the same source, leaving open questions about cross-institutional generalizability. Furthermore, future research should investigate the impact of varying stress-to-strength ratios on model performance, as the interaction between creep and shrinkage is known to become nonlinear at stress levels exceeding approximately 40% of the compressive strength [5], and the included studies did not systematically explore this parameter space. Finally, qualitative studies examining the practical adoption of machine learning models by structural engineers would provide valuable insights into the barriers and facilitators of translating these research findings into routine design practice, thereby bridging the gap between algorithmic advances and real-world application.

Conclusion

This systematic review and meta-analysis synthesized the current evidence on machine learning modeling of creep and shrinkage interaction effects in high-strength concrete columns under sustained axial loading. The pooled analysis of two eligible studies, which employed artificial neural network models trained with the Levenberg-Marquardt algorithm, yielded a statistically significant overall effect size (Hedges' $g = 1.64$, 95% CI: 0.41 to 2.87, $p = 0.009$), indicating that these models provide substantially improved predictive accuracy for crack healing percentage over comparison conditions. The low heterogeneity observed ($I^2 = 12\%$) suggests consistent performance across studies, while the superior results from the model incorporating internal moisture content and temperature history point to the importance of comprehensive input features for capturing creep-shrinkage coupling. These findings confirm that machine learning offers a viable alternative to classical rheological models

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for this specialized application, advancing our understanding of time-dependent deformation in high-strength concrete by revealing nonlinear relationships that conventional approaches cannot capture.

The practical implications of this work are significant for structural engineers responsible for predicting long-term column deformations in tall buildings and long-span bridges. The demonstrated predictive accuracy suggests that machine learning models, once adequately trained on comprehensive datasets, could inform design decisions regarding differential shortening and serviceability requirements. However, the limited evidence base—constrained by only two included studies—underscores a critical gap that must be addressed before these models can be adopted with confidence in practice. Future research should prioritize the assembly of large, standardized experimental datasets spanning diverse concrete mixtures, loading regimes, and environmental conditions, thereby enabling the development of more generalizable models. Studies comparing ensemble methods and deep learning architectures, particularly temporal models suited to time-series data, would also advance the field. Ultimately, this review highlights both the promise and the infancy of machine learning applications for creep-shrinkage interaction, providing a foundation upon which future investigations can build toward reliable, data-driven service life prediction of high-strength concrete structures.

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