DIGITAL PREDICTION OF STRENGTH AND DURABILITY OF RICE HUSK ASH-BASED SUSTAINABLE CEMENTITIOUS MATERIALS USING ARTIFICIAL INTELLIGENCE

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ABSTRACT
The growing demand for low-carbon construction materials has increased interest in supplementary cementitious materials derived from agricultural residues. Rice husk ash (RHA) is promising because of its high silica content, pozzolanic reactivity, porous structure, and potential to reduce Portland cement consumption. However, its performance depends on RHA characteristics, replacement level, water-to-binder ratio, particle size, curing conditions, mixture composition, and exposure environment, making conventional optimization time-consuming.Artificial intelligence (AI), particularly machine learning (ML), offers an emerging approach for predicting material performance and optimizing sustainable cementitious mixtures. Recent studies have applied artificial neural networks, support vector regression, random forest, XGBoost, LightGBM, Gaussian process regression, and hybrid models, mainly for compressive-strength prediction. However, durability-oriented AI applications remain limited, while dataset heterogeneity, incomplete RHA characterization, data leakage, limited external validation, interpretability, uncertainty, and extrapolation remain important challenges.This review critically examines the integration of RHA material science and AI, focusing on mechanical and durability performance, input-variable selection, model comparison, explainable AI, uncertainty quantification, physics-informed ML, and multi-objective optimization. An integrated digital framework is proposed linking RHA characterization, experimental datasets, AI prediction, validation, durability and service-life assessment, sustainability metrics, and mixture optimization. The review highlights a transition from empirical trial-and-error toward ***data-driven, physically informed, and uncertainty-aware material design****. Future research should prioritize standardized RHA datasets, independent validation, durability-focused AI models, physics-informed approaches, probabilistic prediction, and integration with life-cycle assessment and digital decision-support systems.*

Keywords: *Rice husk ash; supplementary cementitious materials; sustainable construction; artificial intelligence; machine learning; strength prediction; durability prediction; explainable AI; uncertainty quantification; physics-informed machine learning; multi-objective optimization; service-life prediction.*

1. INTRODUCTION
Concrete is one of the most widely used construction materials, but its environmental impact is strongly associated with Portland cement production, which consumes substantial energy and generates significant CO_2 emissions. The use of supplementary cementitious materials (SCMs), particularly those derived from agricultural residues, is therefore an important strategy for developing lower-carbon cementitious systems.

Rice husk ash (RHA) is a promising SCM because controlled combustion of rice husk can produce silica-rich ash with significant pozzolanic activity. RHA can improve cementitious performance through pozzolanic reaction, particle-packing, and, depending on its porous structure, internal-curing effects. However, its performance varies considerably with combustion conditions, grinding, particle size, specific surface area, amorphous silica content, and residual carbon. Consequently, RHA replacement level cannot be considered independently of its physicochemical characteristics and mixture conditions.

RHA incorporation can influence workability, hydration, strength, permeability, chloride transport, sulfate and acid resistance, carbonation, shrinkage, and water absorption. These effects depend on RHA content, water-to-binder ratio, curing conditions, cement content, admixture dosage, and exposure environment. Excessive replacement may increase water demand and reduce early-age strength, whereas appropriate processing and replacement can promote later-age strength development and microstructural refinement.The complex interaction among these variables makes conventional experimental optimization time-consuming and resource-intensive. Artificial intelligence (AI), particularly machine learning (ML), offers a complementary approach by learning nonlinear relationships between material characteristics, mixture parameters, curing conditions, and performance. RHA-based studies have employed ANN, ANFIS, SVR, RF, gradient boosting, XGBoost, LightGBM, GPR, and hybrid models, predominantly for compressive-strength prediction.Despite this progress, **RHA-specific AI research remains strongly focused on strength prediction**, while durability-oriented applications remain comparatively limited. Prediction of chloride transport, carbonation, sulfate and acid resistance, shrinkage, permeability, water absorption, and service-life indicators requires further development. Moreover, dataset heterogeneity, incomplete RHA characterization, data leakage, limited external validation, insufficient uncertainty quantification, and poor interpretability may restrict model reliability and transferability.Accordingly, this review critically examines the integration of RHA material science and AI-driven prediction, focusing on mechanical and durability performance, AI methodologies, dataset requirements, explainable and physics-informed AI, uncertainty quantification, and multi-objective optimization. It further proposes an integrated digital framework linking **RHA** characterization, AI prediction, validation, explainability, uncertainty, durability and service-life assessment, life-cycle sustainability, and mixture optimization. The review ultimately identifies a pathway from conventional trial-and-error approaches toward material-aware, explainable, uncertainty-conscious, and sustainability-oriented digital design of RHA-based cementitious materials.

2. RICE HUSK ASH AS A SUSTAINABLE CEMENTITIOUS MATERIAL

Rice husk ash (RHA) is an agricultural-residue-derived supplementary cementitious material produced through controlled combustion of rice husk. Its silica-rich composition, pozzolanic reactivity, fine particles, and porous structure enable partial replacement of Portland cement and contribute to additional C–S–H formation and pore refinement. However, RHA performance depends strongly on its production conditions, physicochemical characteristics, and interaction with mixture constituents. Therefore, for AI-based prediction, RHA should be represented using relevant **chemical, physical, morphological, and processing descriptors**, rather than replacement percentage alone.

2.1 Generation and Characteristics of RHA

Controlled combustion removes the organic fraction of rice husk and produces silica-rich ash containing potentially high levels of amorphous silica. Its reactivity is influenced by combustion temperature and duration, oxygen availability, cooling conditions, grinding, particle-size distribution, specific surface area, amorphous silica content, residual carbon, and chemical composition. Poor combustion may increase residual carbon, while inappropriate thermal treatment can promote crystalline silica formation. Grinding generally improves fineness and surface area, although excessive grinding may increase energy demand and agglomeration. Consequently, RHA from different sources may exhibit substantially different performance even at the same replacement level.

2.2 Pozzolanic and Physical Mechanisms

The primary pozzolanic reaction can be represented as:

$$\textbf{Reactive } SiO_2 + Ca(OH)_2 + H_2O \rightarrow \textbf{additional C–S–H}$$

RHA influences cementitious materials mainly through **pozzolanic reaction, filler/particle-packing effects, and internal curing**. Reactive silica contributes to additional C–S–H formation, fine particles can refine packing and reduce connected porosity, and the porous structure may retain and release water to support hydration. The relative contribution of these mechanisms depends on particle size, porosity, silica reactivity, replacement level, water-to-binder ratio, and curing conditions, resulting in nonlinear interactions suitable for ML-based analysis.

2.3 Effect of RHA Processing on Performance

RHA processing influences workability, reaction kinetics, packing, strength development, and durability and should therefore be incorporated into AI datasets where available. **Amorphous silica, particle size, specific**

ISSN 2394 - 7780

surface area, residual carbon, combustion conditions, grinding intensity, and porosity/morphology are particularly relevant descriptors. Distinguishing between **RHA dosage and RHA quality** can improve the physical interpretation and transferability of AI models across different RHA sources and processing conditions.

3. INFLUENCE OF RHA ON MECHANICAL PERFORMANCE

The mechanical performance of RHA-based cementitious materials depends on RHA characteristics, replacement level, binder composition, water-to-binder ratio, curing conditions, and age. At appropriate replacement levels, pozzolanic reaction, particle packing, and pore refinement can enhance strength, whereas excessive replacement may increase water demand and reduce early-age strength. Thus, RHA performance cannot be represented by replacement percentage alone. Mechanical performance is also the dominant application of AI in RHA research, although most studies focus on compressive strength, with tensile and flexural properties receiving comparatively less attention.

3.1 Compressive Strength

Compressive strength is the most widely studied mechanical property of RHA-based materials and the principal target of RHA-specific AI models. At moderate replacement levels, RHA can improve later-age strength through calcium hydroxide consumption, additional C–S–H formation, particle packing, and pore refinement. Excessive replacement, however, may reduce early-age strength because RHA contributes to pozzolanic activity more gradually than Portland cement and can increase water demand.

Important influencing variables include RHA replacement level, fineness, particle-size distribution, amorphous silica content, specific surface area, residual carbon, cement content, water-to-binder ratio, admixture dosage, aggregate characteristics, curing conditions, and age. Although replacement levels of approximately 5–20% are frequently associated with favorable strength performance, no universal optimum exists because the response depends on RHA characteristics and experimental conditions.

AI studies have employed ANN, ANFIS, SVR, RF, XGBoost, LightGBM, GPR, ensemble, and hybrid models, with generally strong predictive performance. However, comparisons between studies should be made cautiously because dataset size, input variables, preprocessing, and validation strategies differ. Models should therefore be evaluated using multiple error metrics, residual analysis, grouped or independent validation, and external experimental data rather than relying solely on R^2. Incorporating RHA-specific descriptors alongside conventional mixture variables can further improve model relevance and transferability.

3.2 Tensile and Flexural Strength

Tensile and flexural properties provide complementary information on the mechanical behavior of RHA-based materials but remain less investigated than compressive strength. RHA-induced matrix densification and changes in the interfacial transition zone may influence these properties, although the response depends on RHA characteristics, mixture composition, curing, and age. Future datasets should therefore include splitting tensile strength, flexural strength, modulus of elasticity, fracture energy, and stress–strain characteristics alongside compressive strength. Multi-output AI models could subsequently predict several mechanical properties simultaneously, providing a broader basis for structural assessment and mixture optimization.

3.3 RHA Characteristics and Mechanical Response

The mechanical response can be viewed as a hierarchical relationship:

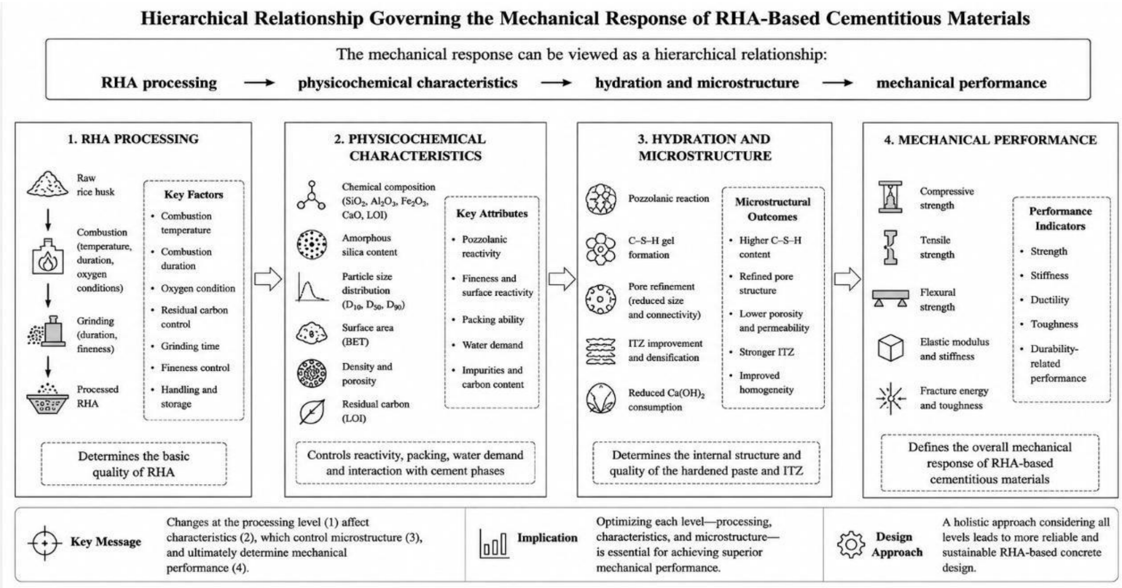


Figure. Hierarchical relationship governing the mechanical response of RHA-based cementitious materials.

Combustion and grinding influence silica phase, particle size, surface area, porosity, and residual carbon, which subsequently affect reaction kinetics, packing, water demand, and pore structure. Future AI models should therefore integrate processing variables + RHA characteristics + mixture proportions + curing conditions to distinguish the effects of RHA dosage from those of material quality and processing history, thereby improving interpretability and potential transferability.

4. DURABILITY OF RHA-BASED CEMENTITIOUS MATERIALS

Durability is essential for evaluating the sustainability of RHA-based cementitious materials because low cement consumption and adequate strength do not necessarily ensure long-term environmental performance. RHA can modify durability through pozzolanic reaction, additional C–S–H formation, and pore refinement, but its effects depend on RHA characteristics, replacement level, mixture composition, curing, exposure conditions, and time. Therefore, durability prediction requires **material, mixture, environmental, and time-dependent variables**.

4.1 Chloride Penetration

RHA can reduce chloride transport through pore refinement and additional C–S–H formation. However, the optimum RHA level for chloride resistance may differ from that for compressive strength. AI models should therefore consider chloride transport as an independent performance target and include variables such as chloride concentration, temperature, relative humidity, and exposure duration.

4.2 Sulfate and Acid Resistance

RHA can influence sulfate and acid resistance by modifying pore structure and binder chemistry and by reducing calcium hydroxide. However, performance depends strongly on exposure concentration, temperature, curing, duration, and chemical environment. AI datasets should therefore distinguish between **different exposure types and severities** rather than treating chemical resistance as a single property.

4.3 Carbonation

Carbonation involves a complex balance between pore refinement and reduced calcium hydroxide availability. While a denser microstructure may restrict CO_2 transport, reduced alkaline buffering can increase carbonation susceptibility. Consequently, carbonation depends on RHA content, binder composition, water-to-binder ratio, curing, relative humidity, CO_2 concentration, and exposure duration. This makes carbonation particularly suitable for **explainable and physics-informed ML**.

4.4 Shrinkage and Water Absorption

RHA's porous structure and high surface area can increase water demand and influence moisture redistribution, shrinkage, and water absorption. Appropriate RHA contents may refine connected porosity, whereas excessive

 ISSN 2394 - 7780

incorporation or inadequate mixture adjustment may adversely affect moisture-related behavior. AI models should therefore consider RHA characteristics together with water-to-binder ratio, admixture dosage, curing, age, and humidity.

4.5 AI Implications for Durability

Different deterioration mechanisms involve different combinations of material, mixture, exposure, and time-dependent variables. **Chloride penetration** requires exposure-aware transport prediction, **sulfate and acid resistance** require environment-specific models, **carbonation** requires time-dependent and potentially physics-informed prediction, while **shrinkage and water absorption** require microstructure- and moisture-sensitive modeling.

Overall, durability prediction requires a more comprehensive representation of RHA-based cementitious systems than conventional strength prediction. Future AI frameworks should integrate **RHA characteristics + mixture parameters + curing + exposure + time** to develop multi-property, uncertainty-aware, and physics-informed models. Rather than optimizing RHA mixtures solely for compressive strength, AI systems should seek balanced solutions considering **strength, durability, workability, embodied carbon, cost, and service life**.

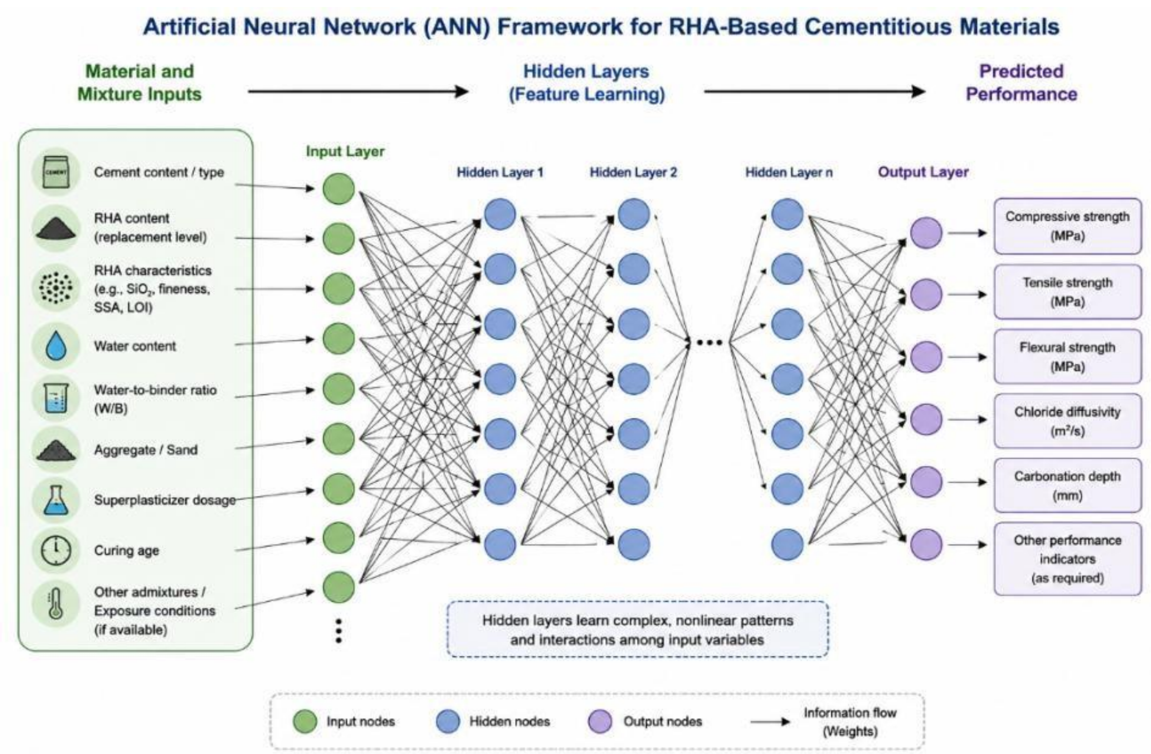
5. ARTIFICIAL INTELLIGENCE FOR CEMENTITIOUS MATERIAL PREDICTION

Artificial intelligence (AI), particularly machine learning (ML), is increasingly used to predict cementitious-material properties from mixture proportions, material characteristics, curing conditions, and experimental parameters. ML can capture nonlinear relationships among variables, making it particularly suitable for RHA-based materials, where performance depends on RHA characteristics, replacement level, water-to-binder ratio, cement content, curing age, and admixture dosage. RHA-specific research has mainly focused on **compressive-strength prediction** using ANN, ANFIS, SVR, RF, gradient boosting, XGBoost, LightGBM, GPR, and hybrid models. However, reported performance should be compared cautiously because datasets, preprocessing, feature selection, and validation strategies differ between studies.

5.1 Artificial Neural Networks

Artificial neural networks (ANNs) model complex nonlinear relationships through interconnected input, hidden, and output layers. A typical RHA framework can be represented as:

Material and mixture inputs → Hidden layers → Predicted performance



Inputs may include cement, RHA, water, aggregates, superplasticizer, water-to-binder ratio, curing age, and RHA physicochemical characteristics. A study using **192 observations** reported strong testing performance for optimized ANN models. However, ANN performance depends on architecture, hyperparameters, training strategy, and dataset quality, while conventional ANN models may be difficult to interpret. Explainable-AI methods can therefore improve understanding of feature contributions.

5.2 Support Vector Regression

Support vector regression (SVR) is a kernel-based method suitable for nonlinear regression and relatively small datasets. RHA studies have reported strong SVR performance, with a comparative study involving approximately **500 observations** identifying SVR and GPR among the better-performing approaches. However, SVR performance depends on kernel selection, feature scaling, hyperparameters, and dataset characteristics, and may decline for highly heterogeneous or out-of-domain data.

5.3 Random Forest

Random Forest (RF) uses multiple decision trees to capture nonlinear relationships and feature interactions. Its advantages include suitability for structured datasets, limited preprocessing requirements, reduced overfitting compared with individual trees, and availability of feature-importance measures. However, RF remains dependent on the training-data domain and has limited extrapolation capability; therefore, high test-set accuracy does not guarantee reliable prediction for new RHA conditions.

5.4 Gradient Boosting, XGBoost and LightGBM

Gradient-boosting methods sequentially construct learners to reduce prediction errors. XGBoost and LightGBM are particularly effective for structured datasets and can capture complex nonlinear interactions. A study involving **1,404 RHA concrete observations** reported approximately **R^2 = 0.95 and RMSE = 5.26 MPa** for a hybrid XGBoost–LightGBM model, while another study with **348 observations** reported strong LightGBM performance and identified influential mixture parameters through feature analysis.

The use of **SHAP and other explainability techniques** further enhances these models by showing how input variables contribute to predictions. Nevertheless, no algorithm can be considered universally superior. Meaningful comparison requires the **same dataset, consistent preprocessing, identical validation procedures, and common performance metrics**.

6. CURRENT AI RESEARCH ON RHA-BASED CONCRETE

AI research on RHA-based concrete has expanded considerably, but it remains predominantly focused on **compressive-strength prediction**. Studies have investigated ANN, ensemble, boosting, hybrid, and metaheuristic approaches using datasets of different sizes and characteristics.

Table 3. Representative AI studies on RHA-based concrete

Study category	Dataset size	AI approaches	Main finding	Critical observation
ANN/ANFIS	192	ANN, ANFIS, regression	Strong prediction performance	Limited dataset
Hybrid ANN	192	ANN + optimization	Testing $R^2 \approx 0.97$	Performance depends on optimization and dataset characteristics
Bagging/boosting	—	DT, Bagging, AdaBoost	Bagging $R^2 \approx 0.93$	Ensemble methods improved prediction
Interpretable ML	348	RF, XGBoost, LightGBM, Ridge	Strong performance by LightGBM	Feature analysis improved interpretation
Hybrid ML	1,404	RF, XGBoost, LightGBM,	Hybrid XGB-LGB $R^2 \approx$ 0.95	Larger dataset, but source

 ISSN 2394 - 7780

		hybrid models		heterogeneity remains relevant
Multi-algorithm	500 + external	12 ML algorithms	SVR/GPR/NuSVR among stronger models	External data provided stronger validation
Metaheuristic ML	291	XGBoost + optimization	APO-XGBoost $R^2 \approx 0.958$	Optimization improves performance but adds complexity
Experimental-ML	359	AdaBoost, DT, GB, KNN, LightGBM, XGBoost	RHA-GGBFS systems experimentally evaluated and predicted	Demonstrates potential for combined SCM systems

The reported studies demonstrate strong predictive potential for RHA-based compressive-strength prediction. However, reported **R^2 values should not be interpreted as a direct ranking of algorithms**, because dataset size, variability, experimental sources, preprocessing, and validation strategies differ substantially between studies.

A key distinction is between **within-dataset accuracy and generalizability**. Models developed from limited RHA sources may perform well for statistically similar test observations but show reduced reliability when applied to different RHA chemistry, processing conditions, curing regimes, or testing protocols. Dataset independence is therefore important; randomly dividing observations from the same experimental campaign between training and testing may produce optimistic performance estimates. **Grouped or source-based validation**, in which observations from the same study or RHA source remain within the same partition, provides a more rigorous assessment of transferability.

Thus, the main challenge is no longer simply achieving a higher R^2. Future RHA-AI research should prioritize **high-quality and standardized datasets, RHA-specific descriptors, independent validation, uncertainty quantification, explainability, and physical consistency**.

7. FROM STRENGTH PREDICTION TO DURABILITY PREDICTION

The strong focus on compressive-strength prediction is a key limitation of current AI-based RHA research. Although strength is important, sustainable cementitious materials must also meet durability, service-life, maintenance, and environmental requirements.

AI has already been applied in broader concrete research to predict chloride diffusion, carbonation, sulfate deterioration, shrinkage, permeability, corrosion indicators, and service-life parameters using approaches such as ANN, SVR, RF, XGBoost, and genetic programming. However, RHA-specific durability datasets remain limited, and models developed for conventional or other SCM-based concretes cannot be directly transferred without experimental validation.

Future RHA-AI research should therefore move toward multi-property and durability-oriented prediction, linking:

RHA characteristics + mixture composition + curing + exposure → strength + transport properties + deterioration + service-life indicators

Such models could simultaneously consider mechanical strength, chloride transport, carbonation, chemical resistance, workability, cement consumption, and embodied carbon. This would shift RHA research from single-property prediction toward performance-based digital material design.

The development of RHA-specific durability datasets, combined with explainable, uncertainty-aware, and physics-informed ML, could further support service-life assessment and multi-objective optimization. The ultimate goal should be to identify RHA mixtures that achieve an appropriate balance between strength, durability, workability, environmental performance, and service life, rather than simply maximizing compressive strength.

8. RECOMMENDED INPUT VARIABLES FOR AI PREDICTION OF RHA-BASED CEMENTITIOUS MATERIALS

The reliability and transferability of AI models depend strongly on the quality of the input variables. A major limitation of existing RHA datasets is that RHA is often represented mainly by its replacement percentage, while differences in its physicochemical characteristics and processing history are overlooked. Since combustion, grinding, particle characteristics, and chemical composition can significantly influence RHA behavior, replacement percentage alone is insufficient for reliable prediction.

A comprehensive AI database should therefore include **binder composition, RHA characteristics, mixture design, processing, curing, exposure, testing, performance, and sustainability variables**. Important RHA descriptors include chemical composition, amorphous silica, LOI, particle size, specific surface area, density, porosity, and combustion and grinding conditions. Mixture and environmental variables should include water-to-binder ratio, aggregates, admixtures, curing conditions, exposure severity, and exposure duration. Mechanical and durability properties should be treated as prediction targets, while cement reduction, embodied carbon, energy demand, and transport distance can support sustainability optimization.

These variables are physically interconnected. For example, combustion affects silica phase composition and residual carbon, while grinding influences particle size and surface area, which subsequently affect water demand, reaction kinetics, packing, and microstructure. Therefore, AI models using only RHA percentage may incorrectly attribute performance differences to dosage rather than material quality.

The database should also clearly distinguish **input, target, and derived variables** to prevent data leakage. Because many published studies lack complete RHA characterization, a practical approach is to establish a **minimum core characterization set**, with additional descriptors retained where available. The preferred data structure is:

RHA processing → RHA characteristics → mixture composition → curing/exposure → measured performance

Such standardized and physically meaningful datasets can improve model interpretability, grouped validation, and transferability, and may be more important for reliable RHA-AI models than simply increasing the number of observations.

9. EXPLAINABLE ARTIFICIAL INTELLIGENCE AND UNCERTAINTY QUANTIFICATION

High predictive accuracy alone is insufficient for reliable engineering application. **Explainable artificial intelligence (XAI)** helps identify why an AI model produces a particular prediction and whether the learned relationships are consistent with material-science principles. This is especially important for RHA because its effects are strongly influenced by interacting variables such as RHA content, fineness, water-to-binder ratio, curing age, and chemical characteristics.

SHapley Additive exPlanations (SHAP) can quantify the contribution of individual variables to model predictions. For RHA-based systems, SHAP can identify the influence of water-to-binder ratio, cement content, RHA replacement, curing age, fineness, and admixture dosage. Global SHAP analysis identifies important variables across the dataset, while local analysis explains individual predictions. However, feature importance should not be interpreted as causality because correlated variables may share predictive information.

Partial dependence and response analysis can further reveal nonlinear relationships between RHA variables and predicted performance, such as an increase in strength up to an optimum RHA level followed by a decline. Because correlated inputs can affect these plots, SHAP dependence analysis, accumulated local effects, and sensitivity analysis may provide complementary insights. Feature-interaction analysis is also important because the effect of RHA depends on variables such as fineness, water-to-binder ratio, curing age, and processing history.

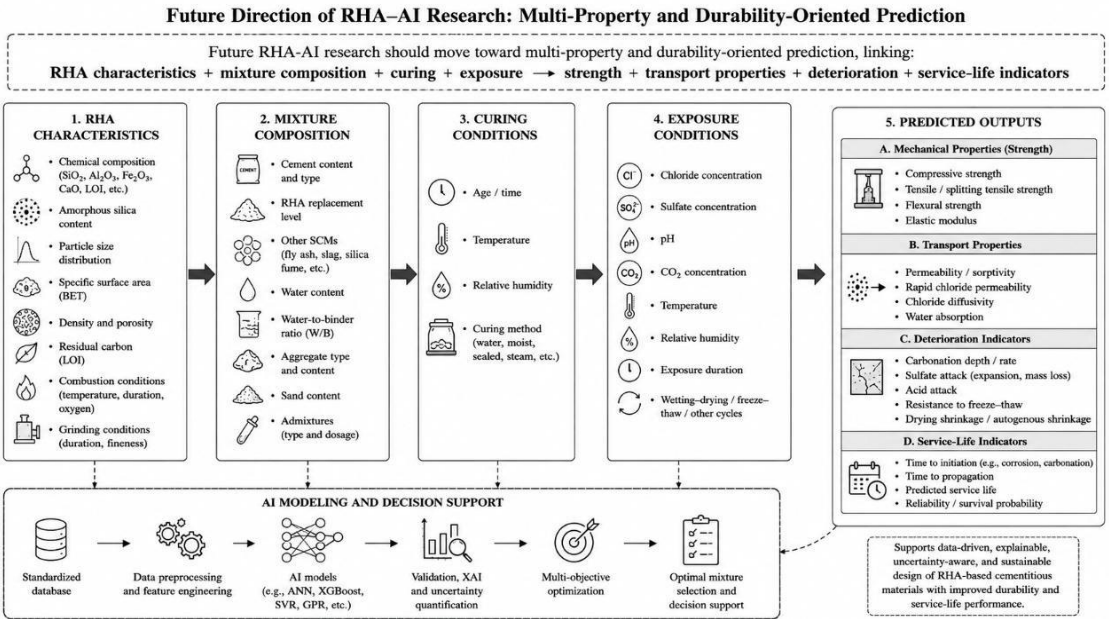
 ISSN 2394 - 7780

10. UNCERTAINTY QUANTIFICATION

AI predictions should ideally be accompanied by **prediction intervals** rather than reported only as single deterministic values. Uncertainty may arise from RHA variability, experimental measurement, laboratory differences, environmental conditions, incomplete characterization, model structure, limited data, and predictions outside the training domain. It can broadly be classified as **aleatoric uncertainty**, associated with inherent material and measurement variability, and **epistemic uncertainty**, associated with limited data or incomplete knowledge.

Approaches such as bootstrap methods, ensemble models, Bayesian regression, GPR, Monte Carlo methods, and conformal prediction can be used to quantify uncertainty. Importantly, uncertainty should be considered throughout **dataset development, model validation, and engineering decision-making**. External validation is essential because a narrow prediction interval from a random train-test split may not indicate reliable performance for a new RHA source or exposure condition. Thus, the desired progression is:

Deterministic prediction → uncertainty-aware prediction → risk-informed engineering decision.



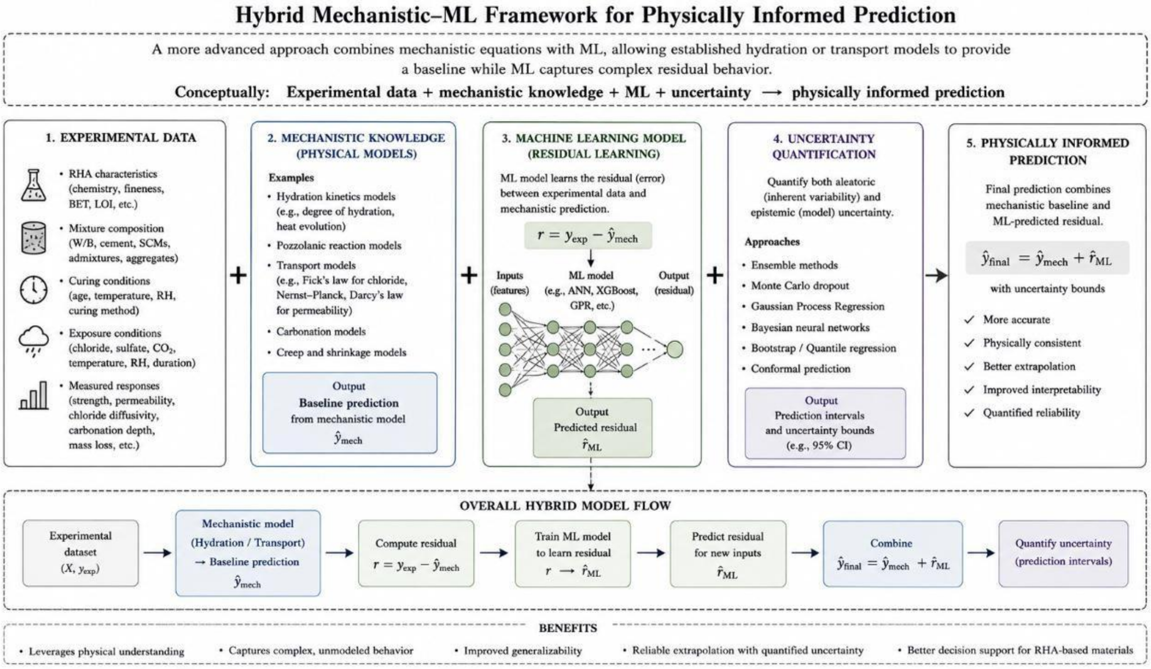
11. PHYSICS-INFORMED MACHINE LEARNING

Purely data-driven AI models learn statistical relationships but may produce physically unrealistic predictions outside their training domain. This is particularly relevant to RHA-based materials, where performance depends on hydration, pozzolanic reaction, pore refinement, moisture transport, chloride diffusion, carbonation, and other deterioration mechanisms. **Physics-informed machine learning (PIML)** addresses this limitation by incorporating scientific knowledge into AI model development.

Physically meaningful variables such as **water-to-binder ratio, curing age, maturity, RHA fineness, amorphous silica content, permeability indicators, and exposure parameters** can be incorporated as physics-informed features. Physical constraints may also be used to restrict predictions to realistic ranges, although such constraints should be defined for the specific material and exposure domain.

A more advanced approach combines mechanistic equations with ML, allowing established hydration or transport models to provide a baseline while ML captures complex residual behavior. Conceptually:

Experimental data + mechanistic knowledge + ML + uncertainty → physically informed prediction



Such hybrid approaches are particularly promising for time-dependent processes such as **chloride transport and carbonation** and may improve model generalizability, physical consistency, and interpretability.

12. MULTI-OBJECTIVE OPTIMIZATION OF RHA-BASED CEMENTITIOUS MATERIALS

The optimum RHA mixture cannot be determined from compressive strength alone. Increasing RHA may reduce cement consumption and embodied carbon, but excessive replacement can adversely affect workability, early-age strength, or durability. Therefore, RHA mixture design should be treated as a **multi-objective optimization problem** involving mechanical performance, durability, workability, cost, and environmental impact.

The optimization framework should aim to **maximize strength, durability, and workability while minimizing cement consumption, embodied CO_2, cost, and other relevant impacts**, subject to practical requirements for strength, durability, workability, material availability, and applicable standards. Because these objectives may conflict, optimization should generate a **Pareto-optimal set** rather than a single universal solution.

AI-based optimization can combine ML prediction models with genetic algorithms, particle swarm optimization, Bayesian optimization, and other evolutionary or metaheuristic methods:

Mixture variables → ML prediction → Performance evaluation → Optimization → Candidate mixture

Although existing RHA studies have demonstrated the potential of ML–optimization combinations, most remain focused on strength. Future work should extend optimization toward **durability, workability, cost, embodied carbon, and service-life performance**.

13. INTEGRATED DIGITAL PREDICTION AND DECISION-SUPPORT FRAMEWORK

A reliable AI framework for RHA-based cementitious materials should integrate **RHA characterization, standardized datasets, AI prediction, validation, explainability, uncertainty assessment, durability evaluation, and multi-objective optimization** rather than focusing only on algorithm selection. The framework begins with chemical, physical, morphological, and processing characterization of RHA, followed by integration with mixture composition, curing, exposure, testing, and performance data. Data quality control should address missing values, duplicates, outliers, unit harmonization, feature redundancy, domain imbalance, and data leakage.

Multiple ML models, including **SVR, ANN, RF, XGBoost, LightGBM, GPR, and hybrid methods**, should be compared using consistent validation procedures. Reliability should be assessed through cross-validation, grouped/source-based validation, independent testing, external validation, and uncertainty analysis. XAI methods such as SHAP, feature importance, response analysis, and interaction analysis can then be used to connect predictions with material mechanisms. Validated models may subsequently support multi-objective optimization of **strength, durability, workability, embodied CO_2, and cost**, producing Pareto-optimal candidate mixtures.

The final outputs can include **recommended RHA range, mixture proportions, predicted performance, uncertainty, and sustainability indicators**, with service-life and LCA assessment incorporated where sufficient data are available. Overall, the framework represents a transition from trial-and-error mixture development toward **data-driven, explainable, uncertainty-aware, and performance-oriented digital material design**. AI should support rather than replace laboratory validation and should be continuously improved using new experimental data.

14. CRITICAL LIMITATIONS OF CURRENT AI RESEARCH

Despite strong reported prediction accuracy, current RHA-AI research faces limitations related to **small and heterogeneous datasets, incomplete RHA characterization, data leakage, limited external validation, overreliance on R^2, poor extrapolation capability, and insufficient durability datasets**. Combining literature data can introduce differences in cement type, RHA processing, curing, testing methods, and exposure conditions, while random train-test splitting may produce overly optimistic results when similar observations occur in both datasets.

Future studies should therefore emphasize **grouped and source-based validation, independent experimental testing, multiple performance metrics, uncertainty assessment, and domain-constrained optimization**. Particular attention is required for long-term durability because current RHA-AI research is considerably more developed for compressive strength than for chloride transport, carbonation, sulfate and acid deterioration, shrinkage, permeability, and service life.

Overall, the main limitation is not the lack of sophisticated algorithms but the **quality, diversity, and independence of the underlying data**. Standardized RHA characterization, external validation, uncertainty quantification, durability datasets, and physically consistent modeling are therefore essential for reliable engineering application.

15. RESEARCH GAPS AND FUTURE RESEARCH DIRECTIONS

RHA-AI research is progressing rapidly but remains limited by **dataset quality, durability prediction, validation, uncertainty, physical consistency, and sustainability integration**. Future work should move beyond compressive-strength prediction toward multi-property models incorporating mechanical and durability performance, supported by standardized RHA descriptors covering chemical composition, fineness, surface area, residual carbon, and processing history.

Greater emphasis is also needed on **grouped and external validation, uncertainty quantification, physics-informed and hybrid ML, durability-focused datasets, and LCA integration**. Digital-twin applications could further connect material models with construction data, sensors, and environmental exposure for continuous performance assessment.

Finally, standardized and publicly accessible benchmark datasets linking **RHA source → processing → characteristics → mixture → curing/exposure → performance** would improve reproducibility and meaningful comparison among AI models.

16. PROPOSED INTEGRATED AI FRAMEWORK

The proposed framework integrates RHA characterization, standardized datasets, AI prediction, validation, explainability, uncertainty, durability, sustainability, and engineering decision-making within a unified digital material-design system. RHA chemical, physical, morphological, and processing characteristics are combined with mixture composition, curing, exposure, testing, and performance data to create a standardized database. After data preprocessing and leakage prevention, ML models such as SVR, ANN, RF, XGBoost, LightGBM, GPR, and hybrid approaches can be developed and compared.

ISSN 2394 - 7780

Model reliability should be evaluated through internal, grouped/source-based, and external validation, supported by multiple performance metrics and uncertainty assessment. XAI methods such as SHAP, feature importance, and interaction analysis can improve physical interpretation, while uncertainty methods can indicate prediction reliability, particularly near or beyond the training domain. Validated models can then support multi-objective optimization of strength, durability, workability, cement consumption, embodied CO_2, and cost, with service-life and LCA assessment incorporated where adequate data are available.

The framework therefore follows RHA characterization → standardized database → data quality control → AI prediction → robust validation → explainable AI → uncertainty quantification → multi-objective optimization → service-life/LCA assessment → digital engineering decision support. AI is intended to complement experimental testing by screening candidate mixtures, identifying influential variables, and prioritizing mixtures for laboratory verification.

17. PRACTICAL IMPLICATIONS FOR SUSTAINABLE CONSTRUCTION

Integration of RHA, AI prediction, durability assessment, and optimization can reduce trial-and-error mixture development by screening combinations of RHA content, water-to-binder ratio, cement, admixtures, and curing conditions. A validated AI system can help identify mixtures that simultaneously satisfy strength, durability, workability, and environmental requirements. However, because RHA properties vary with source and processing, characterization should precede model-based mixture selection, and candidate mixtures should be experimentally validated before practical implementation.

The main practical benefits include faster mixture screening, fewer experiments, identification of influential parameters, uncertainty estimation, and support for lower-carbon mixtures. Integration with LCA can further account for RHA processing, transportation, durability, maintenance, and service life. The practical pathway is therefore RHA characterization → AI-assisted screening → optimized mixtures → laboratory validation → field implementation → performance monitoring.

18. DISCUSSION

The reviewed literature confirms that RHA has strong potential for sustainable construction, but its performance depends on RHA characteristics, mixture composition, curing, and exposure conditions. RHA replacement percentage alone is insufficient to represent material behavior because combustion, silica phase, particle size, surface area, residual carbon, and processing history can substantially influence performance.

Current AI research demonstrates strong potential for compressive-strength prediction using ANN, SVR, RF, XGBoost, LightGBM, GPR, and hybrid approaches, but no algorithm is universally superior. Dataset quality and validation are as important as algorithm selection, particularly because models may perform well within their training domain but poorly for new RHA sources or conditions. Grouped, independent, and external validation are therefore essential.

A major research gap is the limited development of RHA-specific AI models for durability and service-life prediction. Future systems should incorporate exposure conditions and time-dependent variables and use explainable, uncertainty-aware, and physics-informed approaches to improve reliability. Sustainable mixture design should ultimately be treated as a multi-objective problem involving strength, durability, workability, cost, cement consumption, environmental impact, and service life.

Overall, the field should progress from single-property prediction toward integrated, material-aware, uncertainty-conscious, and physics-informed digital material design. The proposed framework should be considered a research roadmap rather than a fully validated engineering system and will require standardized datasets, independent experiments, long-term durability studies, and interdisciplinary collaboration.

19. CONCLUSIONS

This review demonstrates that RHA is a promising supplementary cementitious material, but its performance depends strongly on its physicochemical and processing characteristics and therefore cannot be represented adequately by replacement percentage alone. Current RHA-AI research is dominated by compressive-strength prediction using ANN, SVR, RF, XGBoost, LightGBM, GPR, and hybrid models, with no universally superior algorithm because performance depends strongly on dataset and validation strategy. Reliable application requires standardized RHA characterization, high-quality datasets, grouped and external validation, uncertainty assessment, and explainable and physics-informed AI.

Future research should expand toward durability, service-life, multi-property prediction, and multi-objective optimization, while integrating strength, durability, workability, cement consumption, embodied carbon, cost, and LCA. The proposed framework provides a pathway from RHA characterization and standardized datasets to AI prediction, validation, explainability, uncertainty quantification, optimization, service-life assessment, LCA, and engineering decision support. Ultimately, AI should complement rather than replace experimental research and engineering judgment.

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