

Mechanical and abrasion behaviour of cement and alkali-activated material mixes based on oil refinery waste catalyst: investigation and semi-empirical predictive models

Natalia Szemiot-Jankowska

Wroclaw University of Technology: Politechnika Wroclawska

Masoumeh Khomehchi

Hamedan University of Technology

Murugan Muthu

Khalifa University

Shriram Marathe

NITTE (Deemed to be University): NITTE

Kamil Krzywiński

Wroclaw University of Technology: Politechnika Wroclawska

Lukasz Sadowski

lukasz.sadowski@pwr.edu.pl

Wroclaw University of Technology: Politechnika Wroclawska

Tianyu Xie

Southeast University

Jörg J. Schneider

TU Darmstadt: Technische Universität Darmstadt

Research Article

Keywords: Cement, Spent catalyst, Waste valorization, Abrasion resistance, Alternative binders, Alkali-activation.

Posted Date: August 31st, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10511592/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Mechanical and abrasion behaviour of cement and alkali-activated material mixes based on oil refinery waste catalyst: investigation and semi-empirical predictive models

ABSTRACT

This study presents an investigation into the mechanical performance of alkali-activated material (AAM) and cement mortars incorporating oil refinery waste catalyst or spent equilibrium catalyst (ECAT), an aluminosilicate-rich by-product of oil refining. Through a combination of laboratory experiments and a design-oriented model with physical significance, the structural behaviour of these composites was assessed under mechanical and abrasive loading conditions. OPC-based composites with 20 wt% ECAT demonstrated enhanced compressive (52 MPa) and flexural strength (8 MPa), along with an 18% improvement in abrasion resistance. AAMs exhibited reduced durability due to incomplete activation of ECAT particles, as confirmed by detailed characterisation. The study introduces modified versions of established semi-empirical models specifically calibrated for ECAT-integrated cement and AAM mixes. The models integrate key material parameters (ECAT dosage, particle size, binder type, curing age) and achieved high accuracy with coefficients of variation below 7%. The valorisation of refinery waste in high-performance composite matrices also supports reductions in construction carbon footprints.

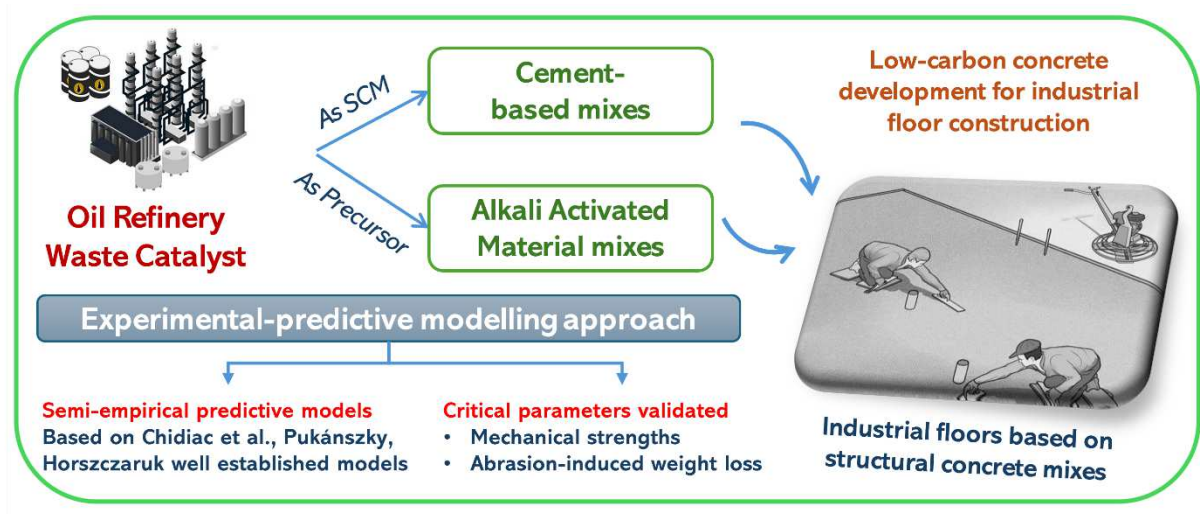
Keywords:

Cement; Spent catalyst; Waste valorization; Abrasion resistance; Alternative binders; Alkali-activation.

Notations:

t	Sample age, days
w/c	Water to cement ratio
f_{28}	28-day compressive strength, MPa
f_c	Predicted compressive strength, MPa
σ_c	28-day flexural strength, MPa
σ_m	Predicted flexural strength, MPa
E	Quantity of ECAT particles, kg
l	Maximum size of ECAT particles, mm
v	Volume fraction of pozzolanic fillers, %
G	Quantity of alkaline activator, kg
W_1	Weight loss due to abrasion, %
B	Empirical adhesion parameter, no unit

GRAPHICAL ABSTRACT



1. INTRODUCTION

Today, urban infrastructure includes structural concrete floors that serve as hard-wearing surfaces [1]. Producing 1 MT of Portland cement results in nearly 0.85 MT of global carbon dioxide (CO₂) emissions, underscoring the need for low-carbon binder for growing infrastructure demands [2]. Researchers have explored industrial by-products to replace cement in concrete mixes, where fly ash and slag densify the concrete microstructure, thereby improving long-term durability while reducing the carbon footprint of concrete production [3]. Alkali-activated material (AAM) has emerged as a promising alternative to cement due to its ability to include industrial waste, which are aluminosilicate materials [4]. This approach aligns with the principles of sustainable production by minimising resource extraction and valorising industrial residues. Researchers are exploring alternative precursors derived from industrial waste and the use of commercial activators to reduce material costs. AAMs, produced by the interaction of aluminosilicate minerals with potassium (K)-based alkaline activators, exhibit enhanced strength, chemical resistance, and environmental benefits relative to cement mixes [5]. Applications of structural concrete based on AAM mixes in urban infrastructure construction can significantly reduce the carbon footprint. A particularly innovative sustainability strategy involves using oil refinery waste catalyst or spent equilibrium catalyst (ECAT), a by-product of the oil refining industry, as a raw material for concrete production. The ECAT contains high levels of alumina and silica, promoting hydration and pozzolanic reactions in concrete when used as a primary or secondary binder [6]. By repurposing ECAT, concrete manufacturers contribute to the principles of the circular economy while addressing the environmental challenges associated with its disposal [7]. Different waste valorisation strategies could have been proposed, including direct incorporation into concrete mixes as a partial replacement for cement or the use of AAM systems [8]. Few earlier studies have shown that the use of ECAT reduces waste and enhances the mechanical properties of cement mixes. For example, research has shown that incorporating ECAT as a cement substitute can improve hydration kinetics, refine the microstructure, and enhance mechanical properties [9]. However, their application in AAM mixes remains relatively unexplored, regarding their effects on strength and abrasion resistance. Incorporating ECAT into such matrices requires a thorough evaluation of its effects on their structural characteristics. Laboratory-scale experiments often include prospective hydration, strength assessments, microstructure and abrasion resistance measurements. Among these, abrasion resistance is a critical property for concrete floors subjected to mechanical wear [10]. The Böhme abrasion test is widely used to quantify concrete's wear resistance under controlled conditions [11]. Abrasion resistance is therefore a decisive service-life parameter, as surface degradation directly translates to reduced load-bearing safety, higher maintenance costs, and premature replacement. Standardised tests, such as the Böhme

method, provide reliable laboratory-scale quantification of this property, but simple predictive modelling enhances understanding by linking wear performance to microstructural and compositional variables [12]. This dual experimental–modelling approach ensures both empirical validation and predictive design capability, which are essential for durable floor systems in structurally demanding environments [13].

Considering the specific applications for floorings, few extensive studies have been reported on the mechanical, durability, and sustainability aspects of cement-based mixes [14]. Significant gaps remain concerning the use of ECAT in these applications as a sustainable supplementary cementitious material (SCM). Comparing OPC and AAM mixes is important because the mechanisms by which ECAT interacts with the binder matrix differ. In OPC, ECAT acts as an SCM, consuming portlandite and refining the C-S-H gel structure. ECAT in AAM mixtures participates in the alkali activation process, contributing to aluminosilicate species that influence gel chemistry, porosity, and microstructure development [15]. By evaluating both systems, this study determines whether ECAT could be prioritized as a pozzolanic additive in OPC matrices or as an active precursor in AAM binders. Such a comparative perspective is essential for guiding practical material selection in abrasion-prone flooring applications [16]. The literature indicates that the effects of ECAT on the abrasion resistance and strength developments of AAM mixes containing commercial alkaline activators have not been investigated. This research gap, and abrasion resistance is a key performance parameter for concrete floors in residential and industrial applications. However, a growing number of recent studies have demonstrated the efficacy of machine learning (ML) and semi-empirical frameworks in predicting the mechanical and abrasion-related performance of cementitious composites [17]. While ML models (such as Random Forest or XGBoost) offer high predictive accuracy, they often require large datasets and operate as ‘black boxes’ with limited physical transparency. In contrast, the semi-empirical models developed are grounded in material-specific parameters which are physically interpretable, and better suited for extrapolation to new mix designs [18]. This is consistent with findings reported in recent literature, where semi-empirical models have been shown to outperform or match ML models in accuracy while offering greater interpretability and generalizability, especially in material-centric contexts [19]. For instance, Gogineni et al. [20] applied ensemble ML techniques, including Random Forest, Gradient Boost, and AdaBoost, to forecast the compressive strength of blended cement matrices, achieving R^2 up to 0.96, thus confirming the predictive power of data-driven models. Xu et al. [21] used XGBoost and other algorithms to model abrasion resistance in concrete matrices containing crushed sand derived from granite rocks, finding factors such as stone powder content and aggregate type influence performance, with model precision exceeding $R^2 >$

0.90. Although these ML techniques exhibit high precision, their dependence on extensive datasets and limited physical interpretability often restricts their practical applicability [22]. Wang et al. [23] presented a fusion of ML and regression analysis to forecast abrasion-induced weight loss under different mix designs, including applications in high-density rubberized concrete, while Peng et al. [24] proposed modified power-law-based formulations to model early-age strength with fitting errors (e.g., fitting error ≤ 0.15 versus traditional models). Asghar et al. [25] further demonstrated that hybridised frameworks integrating artificial neural networks (ANN), gene expression programming (GEP), and XGBoost outperform standalone models for predicting concrete mechanical and durability performance.

The current study advances this domain by introducing semi-empirical predictive models developed based on Chidiac et al. [26], Pukánszky [27], and Horszczaruk [28] for compressive strength, flexural strength, and abrasion loss of cementitious and AAM composites. This framework explicitly incorporates critical variables, including ECAT content, particle fineness, binder type (cement versus AAM), and curing age. These specific models were selected for their compatibility with cement mixes and their ability to embed physically interpretable parameters related to material composition and age-dependent behaviour. The Chidiac model formulation is well-established for strength development in concrete, the Pukánszky model accounts for filler-matrix interactions relevant to flexural behaviour, and the Horszczaruk semi-logarithmic model offers excellent predictive control over abrasion-induced degradation. To ensure reproducibility and model robustness, the experimental dataset for each output property was split into training and test sets at a 75:25 ratio. This allowed reliable estimation of empirical constants while maintaining sufficient unseen data to evaluate predictive accuracy. The hybrid model achieves high accuracy (coefficient of variation $< 7\%$) without requiring extensive datasets, thereby bridging a gap in the predictive modelling of sustainable, wear-resistant cementitious composites. By embedding material-specific, physically interpretable parameters into predictive logic, this study provides a practical, scalable, and scientifically robust tool for next-generation evaluation of concrete performance in abrasive service environments. Silva et al. [29] have employed semi-empirical formulations to correlate elastic modulus with compressive strength in recycled-aggregate concrete—offering a reliable approach that underpins our analogous modelling strategy for ECAT-based composites. Khasawneh [30] demonstrated the practical application of semi-empirical modelling to predict mechanical behaviour in geopolymer concrete—offering a directly relevant precedent for our modelling of ECAT-based alkali-activated systems. Jedrzejko et al. [31] demonstrated the effectiveness of enzyme-induced calcium carbonate precipitation (EICP) with organic and inorganic additives in enhancing crack repair and

mechanical response in cementitious materials, and applied multiscale modelling to capture performance—an approach that complements our ECAT-based composite analysis. To the best of our knowledge, this is the first comprehensive study to integrate the ECAT into both cement-based and alkali-activated binder-based cementitious systems designed for abrasion-sensitive flooring applications, and to couple this material innovation with semi-empirical predictive modelling to assess strength and wear resistance. In this context, the study seeks to bridge the identified research gaps by developing a comprehensive experimental modelling framework to evaluate the performance and predictive behaviour of cement mixes containing ECAT under mechanical and abrasive stress conditions.

The scope encompasses both conventional cement-based and AAM mixes, with ECAT used as a functional additive in a variety of particle sizes and replacement levels. Preliminary trials confirmed an optimal ECAT dose of 20% in cement-based matrices to maintain strength development. At the same time, the inclusion of minimal limestone content was necessary to regulate setting issues in AAM formulations. In contrast to purely data-driven machine learning models such as Random Forests or XGBoost [32], our semi-empirical modelling approach offers several key advantages. Importantly, this study is among the first to adopt a semi-empirical modelling approach specifically calibrated for ECAT-integrated cementitious and AAM systems. This method provides a transparent, physically meaningful alternative to opaque AI-driven models [33], enabling better transferability, interpretability, and engineering relevance in the design of sustainable, wear-resistant composite materials. By integrating physically meaningful parameters with empirical fitting, our models maintain interpretability while capturing non-linear relationships present in the data. This hybrid structure allows for a better understanding of underlying mechanisms and easier extrapolation beyond the training range. While black-box models may sometimes achieve slightly lower error metrics, they lack transparency and can overfit without proper regularization or domain constraints. The semi-empirical formulations developed in this study achieve strong agreement with the experimental dataset, but they are not intended as universally generalizable models. Instead, their primary value lies in their physical interpretability, linking parameters such as ECAT dosage, particle fineness, and curing age to strength and abrasion outcomes. By maintaining mechanistic transparency, these formulations serve as interpretive tools that complement experimental results, supporting hypothesis testing and providing insight into how key parameters govern the behaviour of sustainable cementitious composites under controlled conditions. The specific objectives of this study are fourfold: (i) investigate the mechanical, abrasion and microstructural characteristics of ECAT-integrated cement and AAM mixes; (ii) evaluate surface wear

behaviour using standardized Böhme abrasion testing; (iii) develop and validate hybrid predictive models modified from well-known Chidiac et al. [26], Pukánszky [27], and Horszczaruk [28] models to estimate compressive, flexural, and abrasion resistance based on ECAT parameters, curing age, and binder type; and (iv) provide an interpretive linkage between experimental observations and modeling outcomes through microstructural evidence derived from X-ray diffraction (XRD) and scanning electron microscopy (SEM) tests. By combining rigorous experimental validation with physically interpretable predictive modelling, this study provides a novel, data-efficient methodology for assessing durable, wear-resistant floor construction materials. In addition to laboratory characterisation and modelling, this study emphasizes the practical potential of ECAT-modified cementitious composites as viable structural components in real-world infrastructure. Given their demonstrated strength and abrasion resistance, these materials are particularly well-suited for applications in structural flooring systems, industrial wear-resistant overlays, and pre-fabricated structural panels subjected to repetitive mechanical wear. The combination of mechanical integrity and predictive design capacity makes them promising candidates for load-bearing composite applications in both new construction and retrofitting contexts. Hence, the findings provide both scientific insight into the valorisation of oil refinery waste catalyst and practical tools for predicting performance in concrete infrastructure applications in real life.

2. MATERIALS AND METHODS

2.1. Raw materials

The AAM and cement mixes were prepared using CEM I 52.5R Portland cement, river sand, limestone powder, tap water, and a plasticizer based on sulfonated naphthalene formaldehyde (SNF) and ECAT obtained from Orlen Petrochemicals in Poland. The cement is certified according to EN 197-1 [34], and the water absorption and specific gravity of the fine aggregates were determined according to BS 1097-6 [35]. The average values of these aggregate properties were determined to be 0.43% and 2.65, respectively. Geosil model 14515, a liquid K-based alkaline activator procured from German company Woellner, was used in the alkali activation of ECAT particles. The K_2O and SiO_2 contents of this alkaline solution were 23% and 22% according to the manufacturer. An XRF test was conducted on cement and ECAT samples to determine the oxide composition. The powder sections were loaded onto a circular metal disc and loaded onto the X-ray fluorescence (XRF) instrument (Nex LS model XRF, Rigaku, Japan). Table 1 files the XRF results of the raw materials. ECAT was rich in alumina and silica, and the loss on ignition of ECAT was calculated to be 85% less than that of cement. The loss on ignition was evaluated by heating the samples to 1000 °C in an oven with hot air, and mass changes were documented. The specific

gravity of cement and ECAT was 3.15 and 2.6, respectively, according to the commercial suppliers. The particle size distribution (PSD) of the powder samples shown in Fig. 1a was determined using a particle size analyser (model 1090, Cilas, France) following the laser diffraction method. The mean ECAT size was nearly twice that of cement. XRD analysis was performed on the powder samples to determine the mineral composition. The samples sieved through a 75 μm sieve were scanned at a rate of 0.02° 2θ per minute to 80° 2θ using an XRD instrument (D8 model XRD, Bruker, United States). The XRD results shown in Fig. 1b revealed a high abundance of calcium silicates in cement, while the ECAT was primarily composed of the faujasite mineral. Cement and ECAT samples were scanned at 15 kV using a JSM-7600F SEM (JEOL, Japan) in secondary electron (SE) mode to obtain information on their microstructure. The SEM images of cement showed an angular morphology, while the ECAT particles were spherical.

Table 1 Oxide composition of cementitious materials

Sample	Na ₂ O	K ₂ O	MgO	SO ₃	Al ₂ O ₃	Fe ₂ O ₃	SiO ₂	CaO	Ignition loss
Cement (%)	0.3	0.4	0.8	1.5	3.7	4.6	21.4	64.6	2.7
ECAT (%)	-	-	3.4	3.9	38.1	-	54.2	-	0.4

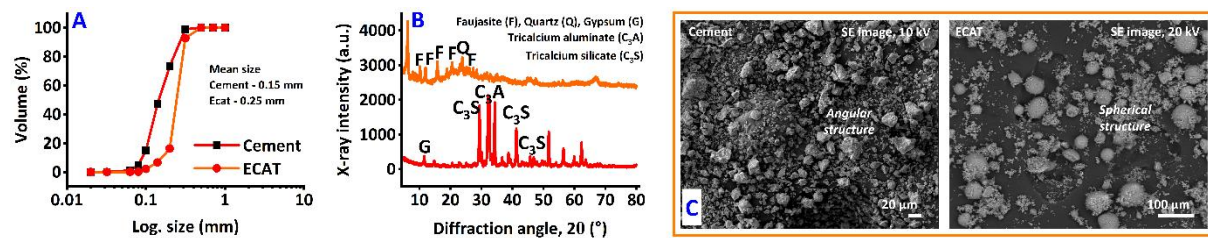


Fig. 1 Results of the (a) laser diffraction, (b) X-ray diffraction, and (c) scanning electron microscopy tests of cement and spent equilibrium catalyst

2.2. Sample preparation

The ECAT particles were screened at 100 μm and 200 μm using a standard sieve to determine the effects of particle size on the development of mechanical strength and abrasion resistance in the cement and AAM mixes. They were designated as E100 and E200 in this study. Table 2 files the specifics of the different mortar samples based on AAM and cement mixes. The sand-to-binder materials of these samples were kept at 3. A minor amount of limestone powder, up to 5 wt%, was added to the AAM mixtures labelled AAM1, AAM2, and AAM3. The alkaline solution of the precursor (namely, ECAT and limestone) was maintained at 1.2 and 1.3 by weight. The

cement was partially restored with ECAT up to 20 wt% in mortar mixes designated as CEM3 and CEM5. The materials were interspersed in a Hobart high-speed blender for up to 3 min. The resulting mixture was loaded into metal moulds of different dimensions and carefully demolded after 24 h. The cement samples were cured in tap water for up to 28 days, while the AAM samples were stored for 28 days in an environmental chamber maintained at 30 °C and 65% relative humidity (RH). Fresh samples were consolidated using a vibrating table.

Table 2 Details of the different mortar mixes

Sample	AAM1	AAM2	AAM3	AAM4	CEM1	CEM2	CEM3	CEM4	CEM5
Cement (g)	-	-	-	-	500	450	400	450	400
E100 (g)	475	475	-	-	-	50	100	-	-
E200 (g)	-	-	475	475	-	-	-	50	100
Limestone (g)	25	25	25	25	-	-	-	-	-
Water (g)	-	-	-	-	215	215	215	215	215
Alkaline Solution (g)	590	650	590	650	-	-	-	-	-
Plasticizer (g)	-	-	-	-	10	10	10	10	10

2.3. Test methods

2.3.1. Flow table test

Fig. 2a shows the flow table apparatus, which conforms to ASTM C1437 [36]. The fresh mortar sample was inserted into the conical truncated tube and positioned at the exact core of this apparatus. The cone was extracted, yielding a newly formed sample, which subsequently dropped 15 times. Mortar flow refers to a change in the median base diameter of the mortar bulk, quantified by measuring at least four diameters at evenly spaced intervals. This is represented as a fraction of the initial centre diameter. Fig. 2b-c shows the flow spread of fresh cement and AAM mortar mixes.

2.3.2. Compression and flexural strength tests

A mortar sample measuring $40 \times 40 \times 40 \text{ mm}^3$ was used to determine compressive strength at 7 and 28 days. A Zwick-Roell universal experiment machine with a loading capacity of 2500 kN was used to crush the hardened samples. During this experiment, a constant load rate of 0.6 MPa/s was maintained as per EN 12390-3 [37]. The average of four replicates was calculated by dividing the compressive failure load by the sample's cross-sectional

area. Fig. 2d-e shows the compressive and flexural strength tests. A prismatic sample of $40 \times 40 \times 160 \text{ mm}^3$ size was used to determine the flexural strength. This sample was tested at 0.5 MPa/s below the three-point load on the universal testing system at 0.6 MPa/s, according to ASTM C348 [38]. The flexural strength of the prismatic sample was calculated using Eq. 1, where P, l, b and d indicate the load at failure, and the effective length, width and depth of the sample.

$$\text{Flexural strength (MPa)} = \frac{3Pl}{2bd^2} \quad (1)$$

2.3.3. Abrasion experiments

Fig.2f illustrates the Bohme test apparatus. A dry mortar sample of size $71 \times 71 \times 71 \text{ mm}^3$ was tested using this apparatus according to EN 14157 [39] to obtain information on weight loss due to abrasion. The sample was pressed onto a grinding wheel, subjected to an abrasive load of 294 N for a specified number of cycles. The weight of the sample before and after the abrasion cycles was recorded to analyse the abrasion resistance of different samples, with mass loss of the concrete used to quantify the level of abrasion. The average of three repetitions was calculated. This test is widely accepted in European and international standards for assessing surface wear durability. It provides a realistic simulation of mechanical wear experienced by flooring and pavement systems under pedestrian and vehicular traffic. The Bohme abrasion resistance is thus a reliable proxy for the long-term and field surface performance of structural flooring units, industrial slabs, and precast pavement components where abrasion-induced deterioration can compromise serviceability and structural integrity, making it a valuable tool for predicting in-service durability of cementitious materials in structural applications [40].

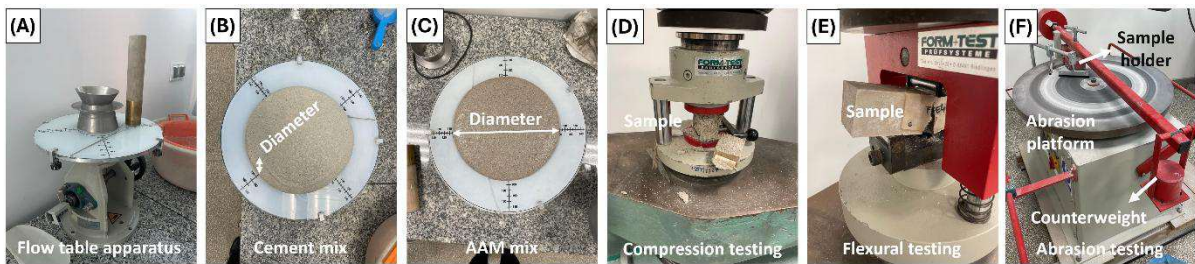


Fig. 2 (a) Flow table apparatus, (b) flow spread of fresh cement mix, (c) flow spread of fresh AAM mix, (d) compressive strength test, (e) flexural strength test, and (f) Bohme test apparatus

2.3.4. Characterization tests

The fragments of the crushed sample were ground and powdered to a size less than 75 μm using a mortar and pestle and a standard sieve, ensuring that the mortar fragments obtained did not contain silica sand. The powdered sample was scanned at 0.02°/min using XRD, covering a 2θ range of 5-80°. A diamond-shaped, sharp saw (Isomet 1000, Buehler, United States) was used to sever the mortar portions derived from the smashed mortar samples. The sections were desiccated and epoxy-impregnated using a vacuum impregnation apparatus (Cast N'Vac 220, Buehler) and allowed to remain uninterrupted for 12 h. The solidified epoxy polymeric material was polished on a metallic plate at 300 rpm, then further polished at 150 rpm using three distinct polycrystalline diamond jets (sizes 1, 3, and 9 μm). The Buehler Metaserv-250 polish device was used. The finely smooth surfaces were subsequently imaged using the SEM instrument operated at 5 kV in backscattered electron transmission (BSE). A carbon bonding agent was used to bond the cured epoxy polymer to the metallic stub inserted into the SEM.

2.4. Prediction modeling framework

To advance interpretive insight and predictive accuracy regarding strength development and wear behaviour in cement and AAM mixes, this study implements a simple semi-empirical modelling approach that extends beyond conventional formulations. While the original models proposed by Chidiac et al. [26], Pukánszky [27], and Horszczaruk [28] have been widely applied to ordinary cementitious systems, they do not explicitly account for the influence of waste-derived aluminosilicate additives, particle fineness, or binder chemistry differences between OPC and AAM matrices. In this work, these models were systematically adapted to incorporate ECAT-specific variables, including dosage, particle size (E100 vs E200), binder type (cement vs AAM), and curing age. A further advancement lies in coupling the predictive equations with microstructural descriptors derived from XRD and SEM analyses. This integration enables the models to remain physically interpretable, as predicted outcomes can be directly linked to observed features such as matrix densification, unreacted ECAT dispersion, or secondary gel formation. By contrast, purely empirical regressions or black-box ML methods may achieve high numerical accuracy but typically lack mechanistic transparency. Each model is developed with a focus on retaining physical transparency and alignment with microstructural observations, thereby offering statistically robust and mechanistically meaningful predictions. This approach achieved low overall coefficients of variation ($< 7\%$), outperforming prior formulations that were either single-system or strength-only focused. Hence, the present framework represents an advancement over existing models by simultaneously (i) embedding material-

specific parameters, (ii) spanning both OPC and AAM systems, and (iii) linking predictions to microstructural evidence, thereby offering a transparent and reliable tool for design optimisation of ECAT-based composites.

3. RESULTS AND DISCUSSION

3.1. Flowability and density

Fig. 3 presents the results of the flow table and density experiments. The average flow diameter of the AAM and cement mixes was determined to be around 171 and 129 mm, respectively. It suggests that AAM mixes showed improved flow of up to 24% compared to cement mixes. There is also an improvement in the flowability of fresh AAM mixes containing up to 15% with increasing doses of the alkaline activator from 590 to 650 g (i.e., a 10% dose increase). E100 and E200 represent the ECAT particles screened at 100 μm and 200 μm , respectively. The addition of fine ECAT particles smaller than 100 μm reduced the flow rate of AAM mixes by up to 19%. The ECAT particles are hollow spheres, and the free water, when mixed, adsorbs to the ECAT surfaces rather than to the cement. This observation can be largely explained by the extensive explicit surface area of ECAT, which is derived from its highly spongy zeolite structure, as previously reported by Tseng et al. [41]. Furthermore, the specific surface area of spherical ECAT particles decreases with decreasing particle size, thereby affecting the flow spread in AAM mixes. As ECAT consists of fine catalyst particles that undergo sintering or agglomeration, indicating that granulation plays a role in its formation, it exhibits a greater affinity for water absorption [42]. In this study, the addition of 20% ECAT reduced the flow diameter of cement mixes by 11%. There was a minor change in the flow of cement mixes when the ECAT sizes were different. When comparing the results for E100 and E200, it was found that the workability of the cement mixes depends on the ECAT dose rather than its surface area. The dry mass of the hardened samples was recorded to analyse the density variations among the different mixes. The average of three replicates was calculated, and the density value was calculated by dividing the sample mass by the volume. The average density of the cement mixes was calculated to be around 2196 kg/m^3 , while that of the AAM mixes was 1908 kg/m^3 . These weight measurements suggest that the cement matrix was 15% denser than the AAM matrix of this study. The underlying reason for this phenomenon remains unclear; however, it may be attributed to variations in the water content within the binder matrix during hydration, influenced by the filler effectiveness and microstructural porosity of ECAT [43]. Replacing up to 20% of the cement with ECAT did not significantly alter the sample density.

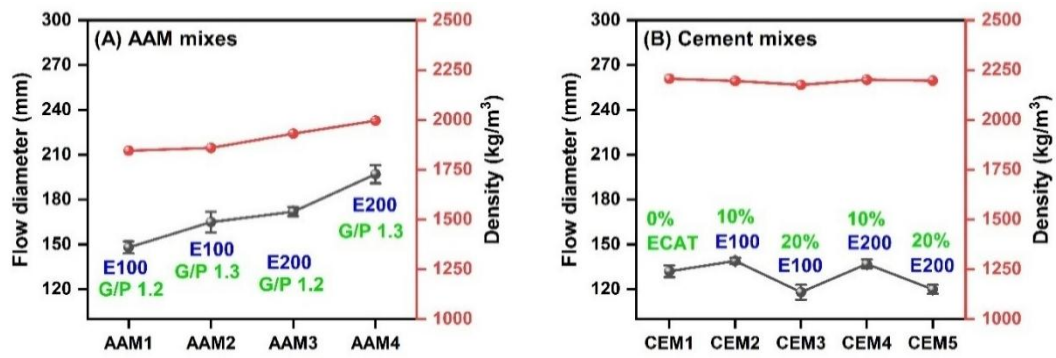


Fig. 3 Flow diameter and hardened density of (a) AAM and (b) cement mixes

3.2. Compressive and flexural strengths

Fig. 4 presents the mechanical properties of the AAM mixes. The average compressive strengths of the AAM samples at 7 and 28 days were 7.3 and 14 MPa, respectively. The compressive strength increased to almost twice as a result of the prolonged storage of AAM samples in a controlled environment. The alkaline solution dose in the AAM1 and AAM2 samples differed, with compressive strengths of 11.3 and 14.5 MPa, respectively, after 28 days. There is an increase in strength of up to 28% due to the addition of more alkaline solution in AAM mixes containing E100 (that is, ECAT size < 100 μm). A similar finding was observed between AAM3 and AAM4 samples prepared with E200. The alkali activation of the ECAT particles was found to be highly dependent on the dose of the K-based alkaline solution. Previous studies reveal that increasing the alkalinity of the activating solution enhances the dissolution of AlO_4 species from the altered zeolite framework and other phases within the ECAT. This selective dissolution process promotes the formation of highly dense, cross-linked aluminosilicate gels, which are essential for developing a strong activation network. At lower alkali concentrations, the gel structure tends to be more heterogeneous, with interconnected pores and a silicon-enriched composition reflecting incomplete dissolution of alumina species. However, at higher alkalinity, the increased $\text{SiO}_2/\text{Al}_2\text{O}_3$ ratio results in the formation of a silicon-rich gel with more cross-linked bonds with low aluminium content, leading to improved material properties [44]. The flexural strength of AAM3 was calculated at 7 and 28 days as 0.7 and 1.6 MPa, respectively. Extending the storage time of the AAM3 sample in a controlled environment increased flexural strength by up to 1.3 times. This may be attributed to the ready dissolution of ECAT in the presence of alkali, due to the dealuminated zeolite structures, which allows Si-Al gel formation and enhanced activation [45]. The mechanical performance of the AAM mixes containing E200 was found to be higher than that of the mixes made with E100, regardless of the alkaline solution dose. The use of E100 could have reduced pore formation in the AAM matrices compared to E200. Still, the results of mechanical tests suggest that the addition of E200

contributed more to alkali activation processes, which are the main drivers of strength development. This effect was observed in the AAM mixes regardless of testing age or alkaline solution dose. Previous studies clearly reveal that the zeolitic structures present in ECAT can facilitate the formation of an aluminium-substituted CSH gel through pozzolanic reactions and/or the development of hydrated aluminate phases [46].

Fig. 5 shows the compressive and flexural strengths of the cement mixes. The addition of ECAT reduced the development of these strengths in cement mixes, regardless of the ECAT dose, according to the literature [53]. Incorporation of E100 and E200 at 20% in cement mixes reduced the compressive strength after 28 days by 9% and 15%, respectively, while the reduction in flexural strength was 6% and 9%, respectively. These experimental findings suggest that the size and dosage of the chosen aluminosilicate material (ECAT) greatly influence the development of the strength of the cement mixes. Extending the cure period from 7 to 28 days increased the compressive and flexural strengths of the plain cement mixture (CEM1) by up to 18% and 14%, respectively. The findings clearly highlight the significant influence of cure time: shorter cure durations result in limited $\text{Ca}(\text{OH})_2$ release from the pozzolanic reaction of ECAT, leading to a higher proportion of ECAT functioning primarily as a filler material. This conclusion is consistent with previous studies on cement mortar samples [28]. However, such improvements in ECAT-based mixes were found to be relatively higher, demonstrating the beneficial role of selecting an aluminosilicate material in modifying cement and concrete systems. The mechanical performance of the AAM and cement mixes improved with decreasing ECAT dose. Therefore, the ECAT content in the concrete mix design must be optimised to avoid weak early-age strength gain. In the present study, the maximum substitution level of 20% ECAT was selected based on a combination of preliminary mechanical screening, flowability tests, and insights drawn from previous investigations on SCMs with comparable mineralogical profiles. Pilot trials conducted with ECAT replacements above 20% resulted in significant reductions in early-age strength (exceeding 25%), poor matrix cohesion, and substandard abrasion performance, rendering those formulations unsuitable for structural-grade applications. Additionally, studies such as Tseng et al. [41] and Roy et al. [47] have reported optimal SCM replacement thresholds for aluminosilicate-rich fillers within the 10–20% range when targeting acceptable trade-offs between sustainability and structural performance. Hence, the 20% threshold in this work was chosen as a practical upper bound to ensure balance between mechanical integrity, durability, and eco-efficiency in both AAM and cement-based systems. ECAT consists of numerous small catalyst particles that undergo sintering or agglomeration, indicating that granulation plays a role in its formation [7]. After 28 days, the compressive strength gain in the AAM mixes was 76% lower than that of the cement mixes, which

explains why the increase in limestone powder in the AAM mortar design could have resulted in improved mechanical performance.

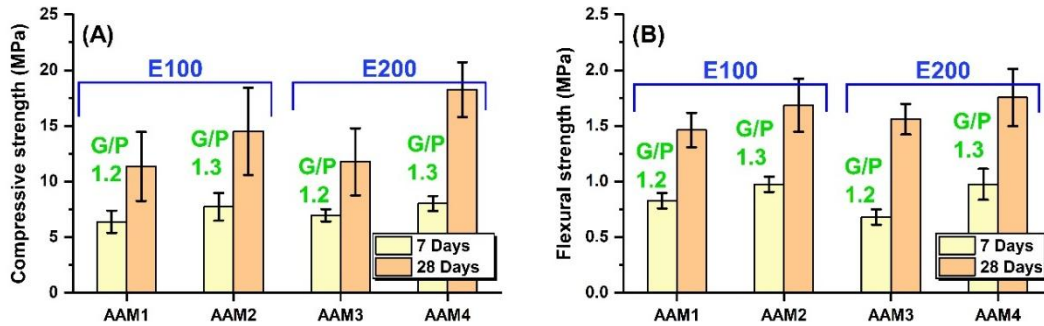


Fig. 4 (a) Compressive and (b) flexural strengths of AAM mixes

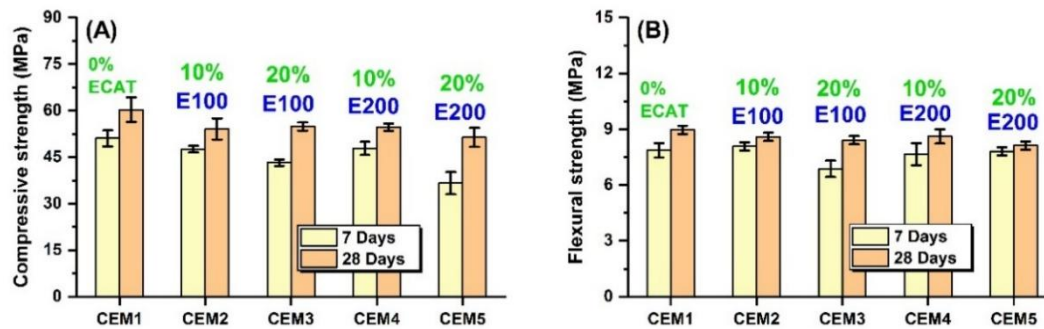


Fig. 5 (a) Compressive and (b) flexural strengths of cement-based mixes

3.3. Abrasion-induced weight loss

Fig. 6 shows the weight loss measurements for AAM and cement mixes at 7 and 28 days. The average weight loss in the AAM and cement mixes at the end of the abrasion experiment was 51% and 6%, respectively. Significant weight loss in the AAM mixes compared to the cement mixes can be primarily attributed to the interaction between ECAT particle size and the AAM matrix structure. The average weight loss of the AAM mixes due to continuous abrasion was calculated to be 9 times higher than that of the cement mixes after 28 days. The loss in sample weight increased by up to 12% when ECAT particles less than 100 μm were used in the development of AAM mixes, regardless of the alkaline solution dose. Therefore, the smaller ECAT particles ($< 100 \mu\text{m}$) used in the AAM mixes likely led to a less stable matrix due to insufficient bonding or packing, potentially increasing susceptibility to abrasion. However, the cement mixes showed improved abrasion resistance when ECAT of any size was included in the mix design. Weight loss due to abrasion in cement mixes was reduced by 18% when cement was replaced with 20% ECAT. This suggests that ECAT acts as an SCM, strengthening and improving the cohesion

of the solid matrix, thereby enhancing abrasion resistance. However, the test findings on AAM mixes suggest that abrasion properties depend on ECAT size rather than on dosage. This also suggests that ECAT particle size plays a key role in determining the durability and abrasion resistance of AAMs. No significant differences in weight loss were observed when the ECAT quantity was modified in both mixes.

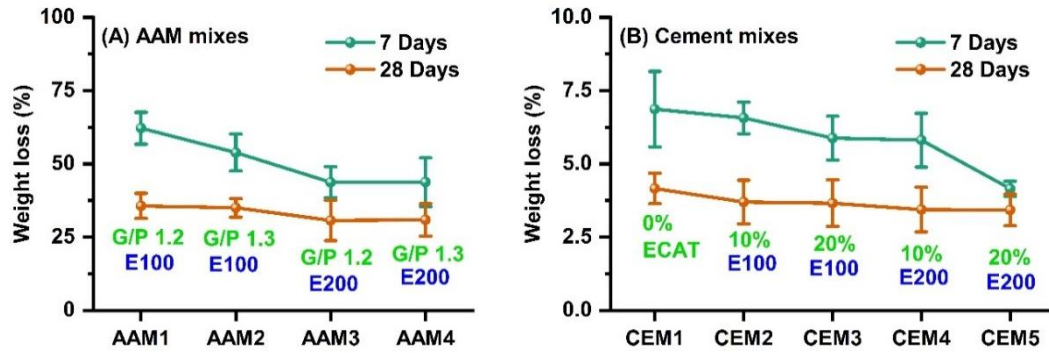


Fig. 6 Weight loss of samples due to abrasion (a) AAM mixes and (b) cement mixes

3.4. Microstructural assessment

Fig. 7 shows the XRD results for the different mortar samples after 28 days. The main X-ray peaks observed at 8.8° , 18.3° , and 23.1° 2θ positions in the plain cement sample (i.e., CEM1) confirmed the formation of ettringite, portlandite, and calcite crystals. In comparison, the intensity of the XRD peaks at 26.6° and 59.9° 2θ positions is attributed to quartz (i.e., silica sand) and calcium silicates (i.e., unhydrated cement). The trace of unhydrated ECAT within the sample matrix (i.e., CEM3) can be determined by analysing the intensities of the XRD peaks at 10.3° , 15.6° , and 20.8° 2θ , as they correspond to faujasite, an aluminosilicate mineral. However, the intensity of the X-ray peaks at these positions was observed to be lower, suggesting that some ECAT particles might have reacted with the cement particles in the binder matrix. The X-ray intensity of portlandite was found to be lower in CEM3 than in CEM1, indicating that ECAT consumed portlandite and led to the formation of secondary CSH in the sample matrix. XRD peaks corresponding to faujasite and quartz were observed primarily in the AAM matrices, confirming the coexistence of unreacted ECAT and alkali-activated aluminosilicate compounds. Fig. 8 illustrates the SEM-BSE images of the cement mortars after 28 days. The mortar samples were polished and analysed via SEM to obtain information on the microstructure. The BSE images showed the assemblage of gaps, cracks, aggregate, and binder components in the sample matrix. They were distinguished by their structure and grey scale levels. The voids, defects, and cracks were completely black. The microstructure of CEM1 does not contain ECAT, but it does contain many unhydrated cement particles, portlandite, and voids distributed

throughout the sample matrix. Clinker compounds were white, while portlandite and other cement hydrates (i.e. CSH) were observed to be grey in colour. Unreacted ECAT particles existed with binder products and aggregates in the CEM4 microstructure, which is found to be denser than CEM1. The interface between the unreacted ECAT and the neighbouring binder products was found to be denser in CEM4 than in the AAM samples (see Fig. 8c). Pozzolanic reaction between the ECAT particles and the surrounding cement components. In contrast, those particles in the AAM matrices might need more alkalis to undergo activation. The AAM microstructure was assembled by unreacted ECAT particles and K-based aluminosilicate hydrates (light grey) and sand (dark grey). As in previous studies, despite dealumination during the service life, the residual zeolite structures in the ECAT remain highly reactive when exposed to alkaline activators of AAMs. This is because the partially distorted and dealuminated aluminosilicate framework readily dissolves, even under relatively low alkalinity conditions [48], facilitating the release of reactive silica and alumina species necessary for alkali activation [49]. These microstructural observations provided critical insight into the mechanical and abrasion-related performance trends discussed earlier. In cement-based mixes, the denser matrix seen in samples with ECAT (e.g., CEM4) can be attributed to pozzolanic reactions between ECAT and liberated portlandite, which contributed to secondary C-S-H formation and enhanced matrix packing, correlating well with the observed improvements in flexural and compressive strength and reduced abrasion losses. Conversely, the presence of unreacted ECAT particles and loosely bound K-based aluminosilicate hydrates in the AAM matrices (e.g., AAM1) corresponds with their lower compressive strength and significantly higher weight loss under abrasion. This confirms that incomplete or non-uniform alkali activation of ECAT, especially at lower alkali dosages or with finer particle sizes, may lead to microstructural heterogeneity and reduced durability. These findings reinforce the importance of optimising the extent of ECAT reactivity and binder densification to improve mechanical resilience and surface wear resistance in sustainable cement-based and AAM systems.

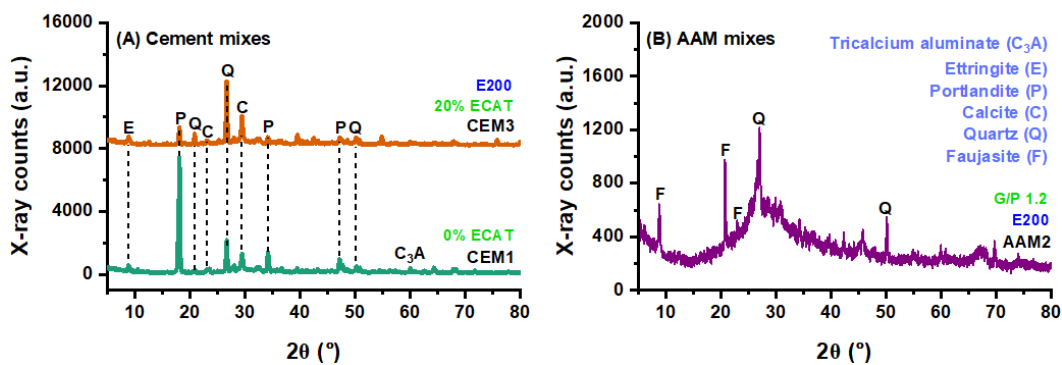


Fig. 7 XRD results of (a) cement and (b) AAM samples based on ECAT

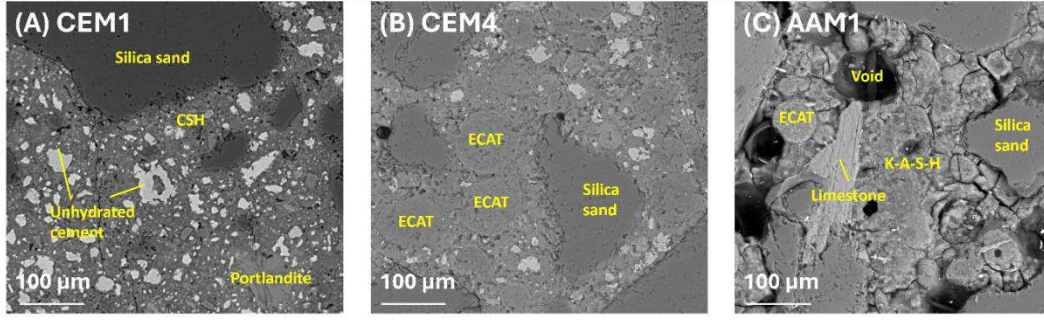


Fig. 8 SEM images revealing the microstructure of (a) CEM1, (b) CEM4, and (c) AAM1

3.5. Semi-empirical modelling

3.5.1. Compressive strength prediction

Chidiac et al. [26] model expressed in Eq. 2 considered sample age (t), 28-day compressive strength (f_{28}), and the water-cement ratio (w/c) to estimate the strength of cement-based mixes at any specific time interval. This model was modified into Eq. 3 to predict the strength of plain cement mixes, where the experimental database is divided into two data sets: a training data set and a test data set, to obtain unknown empirical parameters a_1 and a_2 . The training data set is used to estimate the unknown parameter in Eq. 3, and the test set is used to evaluate the modified model's predictions. The values of a_1 and a_2 are obtained using the training data set, and Eq. 3 is revised into Eq. 4. To consider the effect of ECAT on the compressive strength of cement mixes, the modified model is developed into Eq. 5, where E and l correspond to the quantity and size of ECAT particles. Based on the training data set and Eq. 5, the unknown parameters b_1 and b_2 are obtained, and Eq. 6 is formulated. The results from the developed model are validated by comparison with the test data set. Good agreement is achieved, and the developed model predicts compressive strength with a coefficient of variation of about 6.2% relative to the test data set.

$$f_c = f_{28} \left[\frac{\frac{430w}{c} + 83 - 1031e^{-5.3\left(\frac{1}{t}\right)^{0.7}}}{\frac{430w}{c} - 880} \right] \quad (2)$$

$$f_c = f_{28} \left[\frac{\frac{a_1 w}{c} + 83 - a_2 e^{-5.3\left(\frac{1}{t}\right)^{0.7}}}{\frac{a_1 w}{c} - 880} \right] \quad (3)$$

$$f_c = f_{28} \left[\frac{\frac{-18034w}{c} + 83 - 1030e^{-5.3\left(\frac{1}{t}\right)^{0.7}}}{\frac{-18034w}{c} - 880} \right] \quad (4)$$

$$f_c = (f_{28} + b_1(1 - e^{b_2 El})) \left[\frac{\frac{-18034w}{c} + 83 - 1030e^{-5.3\left(\frac{1}{t}\right)^{0.7}}}{\frac{-18034w}{c} - 880} \right] \quad (5)$$

$$f_c = \left(f_{28} + 3.4 \left(1 - e^{69958El} \right) \right) \left[\frac{\frac{-18034w}{c} + 83 - 1030e^{-5.3\left(\frac{1}{t}\right)^{0.7}}}{\frac{-18034w}{c} - 880} \right] \quad (6)$$

Eq. 7 predicts the compressive strength of the AAM mixes at any specific time interval derived from Chidiac et al. [26] model, where G and E are the quantities of alkaline activator and ECAT used in the AAM mix design. The unknown empirical parameters c_1 and c_2 of this model are obtained using the training data set. Having determined these parameters, Eq. 7 becomes Eq. 8. To consider the effect of ECAT on the compressive strength of AAM mixes, Eq. 9 is developed, where E and l are the quantity and size of ECAT particles. Using the training data set, the unknown parameters d_1 and d_2 are estimated, and Eq. 9 is revised to Eq. 10. The predictions from the developed model are validated against the experimental data set. The model showed strong agreement with the experimental results, yielding an overall coefficient of variation of 6.8% for compressive strength prediction. It is noted that our developed models provided superior predictions of compressive strength at all time intervals than the prediction models presented in Jubori et al. [50] and Gogineni et al. [20]

$$f_c = f_{28} \left[\frac{\frac{c_1 G}{E} + 83 - c_2 e^{-5.3\left(\frac{1}{t}\right)^{0.7}}}{\frac{c_1 G}{E} - 880} \right] \quad (7)$$

$$f_c = f_{28} \left[\frac{\frac{512G}{E} + 83 - 4302e^{-5.3\left(\frac{1}{t}\right)^{0.7}}}{\frac{512G}{E} - 880} \right] \quad (8)$$

$$f_c = f_{28} \left[\frac{\frac{512G}{E} + 83 - 4302e^{-d_1\left(\frac{1}{t}\right)^{0.7} + d_2 l}}{\frac{512G}{E} - 880} \right] \quad (9)$$

$$f_c = f_{28} \left[\frac{\frac{512G}{E} + 83 - 4302e^{-26\left(\frac{1}{t}\right)^{0.67} + 1105l}}{\frac{512G}{E} - 880} \right] \quad (10)$$

The developed model, based on Chidiac et al. [26], and adapted for both cement and AAM systems, demonstrated robust capacity to capture the evolution of compressive strength with curing age and the proportioning of concrete ingredients. For cement mixes, the influence of key parameters, including w/c, E, and l, was incorporated into the model via Eqs. 2-6. For AAM mixes, the model incorporated the parameters G, E, and l, as defined in the equations. 7-10. The model-predicted results for the AAM and cement mixes are shown in Fig. 9. These findings illustrate the development of strength over time, with the prediction curves closely following the experimental data. The strength was observed to improve with the increasing curing age, in agreement with the microstructural densification mechanisms revealed by SEM analysis. Furthermore, the model accurately captured the strength-

reducing effect of a higher ECAT content in cement mixes (due to the partial replacement of reactive clinker) and the compressive strength-enhancing effect in AAM mixes (due to the increased formation of aluminosilicate gels). The prediction overall coefficients of variation was 6.2% for cement and 6.8% for AAM mixes. These values affirm the model's applicability to strength forecasting in sustainable construction design without the need for large data sets [51].

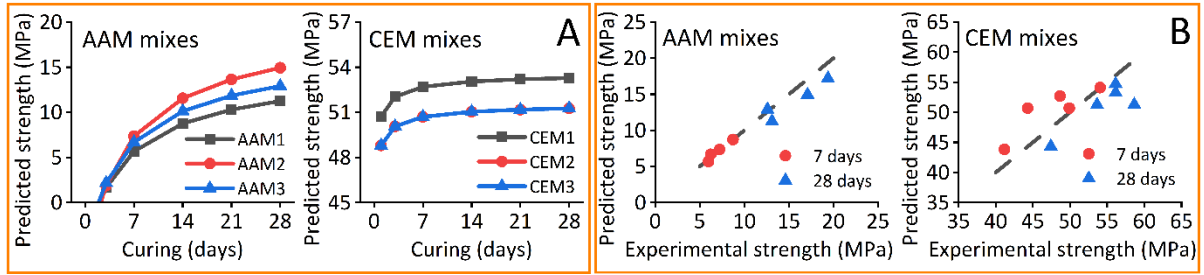


Fig. 9 Compressive strength modeling results of AAM and cement mixes (a) strength predicted over time and (b) experimental information versus predicted information

3.5.2. Flexural strength prediction

Eq. 11, based on Pukánszky [27] model, predicts the flexural strength of cement mixes containing pozzolanic fillers at any curing age, where σ_c and σ_m are the corresponding strengths at a specific time interval and at 28 days. B and v correspond to the empirical adhesion parameter and the volume fraction of such fillers. This prediction model was modified to Eq. 12 to determine the flexural strength of cement-based mixes, where t, E, and l again correspond to sample age, ECAT quantity, and ECAT size, respectively. The experimental database is split into two datasets: a training dataset and a test dataset, to obtain the unknown empirical parameters g_1 , g_2 , and g_3 . The training data set is used to estimate the unknown parameter in Eq. 12, and the test set is used to evaluate the modified model's predictions. The values of g_1 , g_2 , and g_3 in Eq. 12 are obtained from the training data set, and the resulting model is given by Eq. 13. The strength results obtained from the proposed prediction model are validated against the experimental data set. A strong correlation was observed between the predicted and experimental values, with a coefficient of variation of 1.7% or less.

$$\sigma_c = \sigma_m \left(\frac{1-v^{2/3}}{1+2.5v^{2/3}} \right) e^{Bv^{2/3}} \quad (11)$$

$$\sigma_c = \sigma_m \left(\frac{t}{4+0.85t} \right)^{g_1} (1-IE)^{g_2} \left(\frac{1-E^{2/3}}{1+2.5E^{2/3}} \right) e^{g_3 E^{2/3}} \quad (12)$$

$$\sigma_c = \sigma_m \left(\frac{t}{4+0.85t} \right)^{0.2} (1 - lE)^{3736} \left(\frac{1-E^{2/3}}{1+2.5E^{2/3}} \right) e^{3.2E^{2/3}} \quad (13)$$

Based on the Pukánszky [27] model, the flexural strength of the AAM mixes is predicted using Eq. 14, where t , G , and E correspond to sample age, alkaline activator quantity, and ECAT quantity, respectively. The training data set is used to estimate the unknown parameter in Eq. 14, and the test set is used to evaluate the modified model's predictions. The values of k_1 , k_2 , k_3 , and k_4 in Eq. 14 are obtained from the training data set, and Eq. 14 is then rewritten as Eq. 15. The predictions from the developed model are validated by comparing them with the experimental dataset. The model demonstrates strong alignment with the experimental information, showing a general coefficient of variation for flexural strength prediction of 6.8%. The models in this study demonstrated superior accuracy in predicting flexural strength across all time intervals compared with those reported by Roy et al. [47].

$$\sigma_c = k_1 \left(\frac{t}{4+0.85t} \right)^{k_2} \left(1 - \frac{G}{E} \right)^{k_3} \left(\frac{1-\left(\frac{G}{E}\right)^{2/3}}{1+2.5\left(\frac{G}{E}\right)^{2/3}} \right) e^{k_4 \left(\frac{G}{E}\right)^{2/3}} \quad (14)$$

$$\sigma_c = -4623 \left(\frac{t}{4+0.85t} \right)^{1.8} \left(1 - \frac{G}{E} \right)^{-152} \left(\frac{1-\left(\frac{G}{E}\right)^{2/3}}{1+2.5\left(\frac{G}{E}\right)^{2/3}} \right) e^{-4.12 \left(\frac{G}{E}\right)^{2/3}} \quad (15)$$

The predictions of flexural strength were modelled using a Pukánszky [35] model developed to incorporate key parameters, including E , l , t , and σ_m , along with binder information. The generalised expressions employed to model the cement, and AAM systems were detailed in Eqs. 11-15, and the prediction results are shown in Fig. 10a-b. For AAMs, the predicted strength increased with both ECAT quantity and sample age, consistent with observations of compressive strength and microstructural evolution [43]. In contrast, the cement mixes showed slight reductions in flexural strength with increasing ECAT content, due to reduced binder reactivity [52], although the model fit remained strong. The predictive accuracy was notably high, with an overall coefficient of variation of 1.7% for cement and 6.8% for AAM, validating the model's reliability for strength prediction. These findings substantiate that the modelling framework effectively quantifies performance variations due to ECAT size and dosage, while remaining grounded in physical mechanisms.

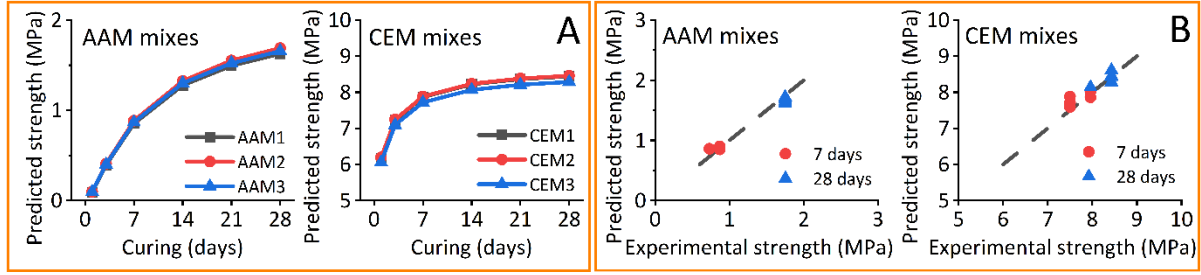


Fig. 10 Flexural strength modeling results of AAM and cement mixes (a) strength predicted over time and (b) experimental information versus predicted information

3.5.3. Abrasion-induced weight loss prediction

According to Horszczaruk [28] for high-performance concrete, the weight loss (W_1) can be formulated as Eq. 16. Considering Eq. 16 for cement mixes, the experimental database is split into two data sets: a training data set and a test data set to obtain unknown empirical parameters x_1 and x_2 . The training data set is used to estimate the unknown parameters in Eq. 16, and the test set is used to evaluate the modified model's predictions. The values of x_1 and x_2 are obtained using the training data set, and Eq. 17 is constructed. This modified model, as shown in Eq. 18, accounts for ECAT's effect on the weight loss of cement mixes. Using the training data set, the unknown parameters y_1 and y_2 are estimated, and Eq. 18 is revised to Eq. 19. The model's performance is validated by comparing the results with the experimental dataset. The model demonstrates strong agreement with the test data, achieving a coefficient of variation of 4.8% in predicting weight loss.

$$w_1 = x_1 [\ln(t + 1)]^{x_2} \quad (16)$$

$$w_1 = 0.86 [\ln(t + 1)]^{-0.98} \quad (17)$$

$$w_1 = 0.86 [\ln(t + 1)]^{-0.98} + (1 - l)^{y_1} (1 - E) y_2 \quad (18)$$

$$w_1 = 0.86 [\ln(t + 1)]^{-0.98} - 3.6(1 - l)^{40416} (1 - E) \quad (19)$$

Considering the basis of Horszczaruk [28], the abrasion-induced weight loss of the AAM mixes was predicted using Eq. 20. The training data set is used to estimate the unknown parameters in Eq. 20. In contrast, the test data set is utilised to assess the predictive accuracy of the modified model. The constants z_1 , z_2 , and z_3 in Eq. 20 are derived from the training data, yielding Eq. 21. The results of the developed model are validated by comparison with the test data set. Good agreement is achieved, and the developed model predicts weight loss with an overall

coefficient of variation of 6.1% relative to the test data set. The models developed in this study demonstrated greater accuracy in predicting weight loss across all time intervals than the models reported by Xu et al. [21].

$$w_1 = z_1 \frac{G}{E} [\ln(t + 1)]^{z_2} + (1 - l)^{z_3} \quad (20)$$

$$w_1 = -0.13 \frac{G}{E} [\ln(t + 1)]^{0.9} + (1 - l)^{1159} \quad (21)$$

The abrasion resistance, modelled by the Horszczaruk [28] developed, was sensitive to both age-dependent matrix development and ECAT incorporation characteristics. Semi-logarithmic expressions accounting for the key parameters E , l , and binder information are presented in Eqs. 16-21. Fig. 11 shows the predicted trends in abrasion-induced weight loss for the different samples in this study. The modelled weight loss showed excellent agreement with the experimental information, decreasing with curing time and increasing the ECAT content (in AAMs), or decreasing the ECAT size (in cement). The obtained results reinforce the precision of the predictions, with overall coefficients of variation of 4.8% and 6.1% for the cement and AAM mixes, respectively. This validated modelling framework, grounded in microstructural interpretations (e.g., densification and phase evolution, shown in Section 3.4), offers a practical tool for forecasting wear performance in cementitious flooring systems, especially where sustainability, precision, and reliability are critical. However, it is important to note that, while the semi-empirical formulations developed in this study demonstrate high agreement with the experimental dataset, they are not intended to be universally generalizable predictive models. Their primary contribution lies in providing mechanistic interpretability by explicitly linking ECAT dosage, particle size, binder type, and curing duration to mechanical strength and abrasion outcomes. In this sense, the models should be viewed as interpretive frameworks that complement experimental testing, helping to rationalize observed property trends and highlight the influence of key parameters under controlled laboratory conditions.

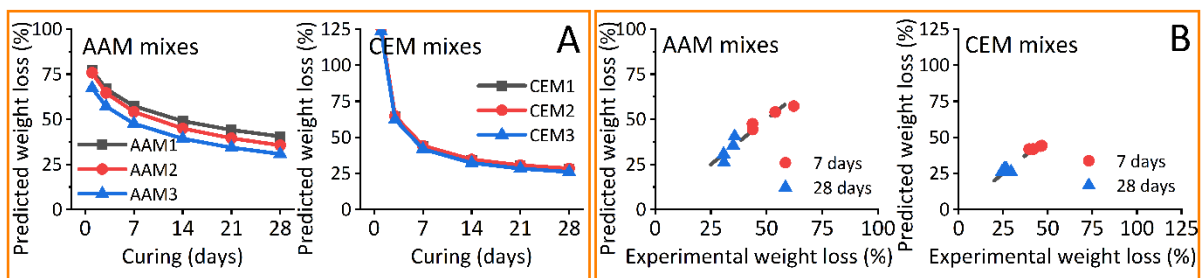


Fig. 11 Abrasion-induced degradation modeling results of AAM and cement mixes (a) weight loss predicted over time and (b) experimental information versus predicted information

4. CONCLUSIONS

This study developed a unified experimental and semi-empirical modelling framework to evaluate the mechanical performance and abrasion resistance of sustainable cementitious and alkali-activated material composites incorporating ECAT, a refinery-derived aluminosilicate waste. By leveraging both microstructural insights and performance metrics, the study provides a detailed characterisation of ECAT-modified systems across varied binder regimes and curing conditions. The following key conclusions and future research directions can be drawn:

- The incorporation of ECAT, particularly in finer size fractions, led to notable improvements in mechanical strength in cement-based composites, reaching compressive and flexural strengths of 52 MPa and 8 MPa, respectively, with 20 wt% ECAT substitution at 28 days. In alkali-activated systems, the reduced particle size (E100) promoted superior strength development, due to enhanced reactivity and improved matrix packing, resulting in up to a 26% increase in compressive strength compared to coarser ECAT. These effects are attributed to better particle dispersion, increased pozzolanic activity in cement, and more favourable nucleation sites for aluminosilicate gel formation in AAMs. Abrasion resistance also improved in cement mixes, with up to 18% reduction in weight loss. However, AAMs showed higher degradation due to unreacted ECAT particles and weaker bonding, as confirmed by SEM and XRD analyses.
- These ECAT-based composites, owing to their tailored microstructure and improved wear resistance, show significant promise for use in structurally demanding environments, such as industrial flooring, precast paving blocks, pedestrian walkways, and overlays in traffic-prone areas where abrasion resistance is critical.
- The composite nature of the system, comprising mineral binder matrices reinforced with optimised ECAT fractions, confirms its structural potential. The synergy between binder phase development, filler interaction, and physical packing enables a robust material system capable of withstanding mechanical loads and surface wear, supporting their relevance in composite structural applications.
- A major contribution of this work is the development of interpretable prediction models based on Chidiac, Pukánszky, and Horszczaruk formulations. These models incorporate key design parameters ECAT dosage, particle fineness, curing age, and binder type and were validated against experimental results with average coefficients of variation < 7%. Their physically grounded formulations allow better extrapolation and practical adaptability to real-world mix designs.
- Environmentally, substituting cement with up to 20% ECAT offers meaningful sustainability gains. Assuming typical clinker-related CO₂ emissions of ~0.85 kg CO₂/kg cement, this replacement can lower CO₂

emissions by approximately 170 kg per MT of binder. Additionally, the reuse of refinery waste in value-added construction products contributes to circular economy targets by diverting hazardous waste from landfills and reducing the need for virgin raw materials.

- Despite these strengths, the study has limitations. Long-term durability tests under aggressive environmental conditions (e.g., freeze-thaw and carbonation) and performance validation under real field conditions were not conducted. The scaling of laboratory results to full-scale applications remains to be established. Moreover, the inherent variability in ECAT composition across sources may affect repeatability, warranting further studies on compositional standardisation.
- Future research directions include pilot-scale field trials, integration of ECAT composites with fibre-reinforcement strategies for crack control, and the use of digital modelling tools, such as AI-assisted mix design or finite element analysis, to simulate service behaviour. These directions will help enhance the structural reliability and design efficiency of sustainable composite systems.
- Finally, the role of ECAT particle size was observed to critically influence both abrasion resistance and strength, as it affects reactivity, dissolution rate, and packing density. Mechanistically, finer ECAT fractions provide greater surface area for chemical activation and denser packing in the matrix, thereby promoting better stress transfer and reduced porosity. While a schematic illustration of this mechanism is beyond the scope of this article, it is recommended that future publications or supplementary materials visualise this structure-property relationship more intuitively.

This work lays a foundation for high-performance, environmentally beneficial cementitious composites leveraging ECAT, combining rigorous experimentation with transparent, adaptable modelling to support future structural innovations.

REFERENCES

1. Anderson, Sherika, and Adeyemi Adesina. 2026. Advancements in multifunctional sustainable and smart concrete for disaster-resilient urban infrastructure: A review. *Next Materials* 13: 102811. <https://doi.org/https://doi.org/10.1016/j.nxmte.2026.102811>.
2. Hassan, Faheem, Muhammad Nasir Amin, Hilal Khan, Muhammad Hassan Khan, and Shoaib Irfan. 2026. Development of CO₂ Mineralised concrete for carbon sequestration: Thermogravimetric analysis and life cycle assessment. *Results in Engineering* 30: 110120. <https://doi.org/https://doi.org/10.1016/j.rineng.2026.110120>.
3. Tosti, Lorenzo, André van Zomeren, Jan R Pels, and Rob N J Comans. 2021. Evaluating Biomass Ash Properties as Influenced by Feedstock and Thermal Conversion Technology towards Cement Clinker Production with a Lower Carbon Footprint. *Waste and Biomass Valorization* 12: 4703–4719. <https://doi.org/10.1007/s12649-020-01339-0>.
4. Vaičiukynienė, D, D Nizevičienė, A Kantautas, A Kielė, and V Bocullo. 2021. Alkali Activated Binders Based on Biomass Bottom Ash and Silica By-Product Blends. *Waste and Biomass Valorization* 12: 1095–1105. <https://doi.org/10.1007/s12649-020-01042-0>.
5. Bernal, Susan A, Erich D Rodríguez, Ruby Mejia de Gutiérrez, John L Provis, and Silvio Delvasto. 2012. Activation of Metakaolin/Slag Blends Using Alkaline Solutions Based on Chemically Modified Silica Fume and Rice Husk Ash. *Waste and Biomass Valorization* 3: 99–108. <https://doi.org/10.1007/s12649-011-9093-3>.
6. Abdolpour, Hassan, Murugan Muthu, Paweł Niewiadomski, Łukasz Sadowski, Łukasz Hojdys, Piotr Krajewski, and Arkadiusz Kwiecień. 2023. Performance and life cycle of ultra-high performance concrete mixes containing oil refinery waste catalyst and steel fibre recovered from scrap tyre. *Journal of Building Engineering* 79: 107890. <https://doi.org/https://doi.org/10.1016/j.jobe.2023.107890>.
7. Matos, Ana Mafalda, Sandra Nunes, Carla Costa, and José L Barroso Aguiar. 2021. Durability of an UHPC containing spent equilibrium catalyst. *Construction and Building Materials* 305: 124681. <https://doi.org/https://doi.org/10.1016/j.conbuildmat.2021.124681>.
8. Mishra, Jyotirmoy, Smruti Sudeshna Mohapatra, Bharadwaj Nanda, and Sanjaya Kumar Patro. 2026. Compressive Strength and Microstructural Properties of Geopolymer Binder Manufactured with Rice Husk Ash-Based Alkaline Activator at Room Temperature. *Waste and Biomass Valorization* 17: 1157–1176. <https://doi.org/10.1007/s12649-025-03193-4>.

9. Michałek, Andrzej, Shriram Marathe, Natalia Szemiot-Jankowska, Murugan Muthu, Kamil Krzywiński, and Łukasz Sadowski. 2025. Influence of Alkaline Activator on the Performance of Alkali Activated Material Based on Oil Refinery Waste Catalyst. In *Early-Age and Long-Term Cracking in RC Structures*, ed. Fragkoulis Kanavaris, Agnieszka Jędrzejewska, Farid Benboudjema, and Miguel Azenha, 337–347. Cham: Springer Nature Switzerland.
10. Nochaiya, Thanongsak, Tawat Suriwong, and Phongthorn Julphunthong. 2022. Acidic corrosion-abrasion resistance of concrete containing fly ash and silica fume for use as concrete floors in pig farm. *Case Studies in Construction Materials* 16: e01010. <https://doi.org/https://doi.org/10.1016/j.cscm.2022.e01010>.
11. Kupers, Laura, Bram Doms, and Julie Piérard. 2018. Wear Resistance of Concrete Floors: Drafting the Guidelines for Concrete Design and Surface Finishings. In *High Tech Concrete: Where Technology and Engineering Meet*, ed. D. A. Hordijk and M. Luković, 2316–2324. Cham: Springer International Publishing.
12. Duran, Atis Cengiz, Karahan Okan, Ari Kamuran, Celik Sola Özlem, and Bilim Cahit. 2009. Relation between Strength Properties (Flexural and Compressive) and Abrasion Resistance of Fiber (Steel and Polypropylene)-Reinforced Fly Ash Concrete. *Journal of Materials in Civil Engineering* 21. American Society of Civil Engineers: 402–408. [https://doi.org/10.1061/\(ASCE\)0899-1561\(2009\)21:8\(402\)](https://doi.org/10.1061/(ASCE)0899-1561(2009)21:8(402)).
13. Horszczaruk, Elżbieta. 2005. Abrasion resistance of high-strength concrete in hydraulic structures. *Wear* 259: 62–69. <https://doi.org/https://doi.org/10.1016/j.wear.2005.02.079>.
14. Jayasinghe, Amila, John Orr, Will Hawkins, Tim Ibell, and William P Boshoff. 2022. Comparing different strategies of minimising embodied carbon in concrete floors. *Journal of Cleaner Production* 345: 131177. <https://doi.org/https://doi.org/10.1016/j.jclepro.2022.131177>.
15. Rodríguez, Erich D, Susan A Bernal, John L Provis, John D Gehman, José M Monzó, Jordi Payá, and M Victoria Borrachero. 2013. Geopolymers based on spent catalyst residue from a fluid catalytic cracking (FCC) process. *Fuel* 109: 493–502. <https://doi.org/https://doi.org/10.1016/j.fuel.2013.02.053>.
16. Tashima, M M, J L Akasaki, J L P Melges, L Soriano, J Monzó, J Payá, and M V Borrachero. 2013. Alkali activated materials based on fluid catalytic cracking catalyst residue (FCC): Influence of SiO₂/Na₂O and H₂O/FCC ratio on mechanical strength and microstructure. *Fuel* 108: 833–839. <https://doi.org/https://doi.org/10.1016/j.fuel.2013.02.052>.

17. Wang, Yifeng, Kan Wang, and Chuck Zhang. 2024. Applications of artificial intelligence/machine learning to high-performance composites. *Composites Part B: Engineering* 285: 111740. <https://doi.org/https://doi.org/10.1016/j.compositesb.2024.111740>.
18. Wang, Zheng, Yuanjie Xiao, Umar Faruk Aminu, Qingyu He, Yunbo Li, and Wenqi Li. 2024. Prediction of resilient modulus and critical dynamic stress of recycled aggregates: Experimental study and machine learning methods. *Transportation Geotechnics* 49: 101363. <https://doi.org/https://doi.org/10.1016/j.trgeo.2024.101363>.
19. Nguyen, Ngoc-Hien, Joaquín Abellán-García, Seunghye Lee, and Thuc P Vo. 2024. From machine learning to semi-empirical formulas for estimating compressive strength of Ultra-High Performance Concrete. *Expert Systems with Applications* 237: 121456. <https://doi.org/https://doi.org/10.1016/j.eswa.2023.121456>.
20. Gogineni, Abhilash, Indra Kumar Panday, Pramod Kumar, and Rajesh kr. Paswan. 2024. Predictive modelling of concrete compressive strength incorporating GGBS and alkali using a machine-learning approach. *Asian Journal of Civil Engineering* 25: 699–709. <https://doi.org/10.1007/s42107-023-00805-z>.
21. Xu, Xubo, Jicheng Xie, Yasen Tang, Liufen Luo, Zheng Chen, and Jiawen Li. 2024. Experimental Study and Machine Learning-Based Prediction of the Abrasion Resistance of Manufactured Sand Concrete. *Buildings* 14. <https://doi.org/10.3390/buildings14113433>.
22. Peng, Yiming, Minfei Liang, and Cise Unluer. 2026. Machine learning-enabled pathways for low-carbon concrete. *npj Materials Sustainability* 4: 29. <https://doi.org/10.1038/s44296-026-00109-8>.
23. Wang, W T, Z P Zhu, Z Liu, Y J Shang, Y C Liu, and J F Dong. 2024. Experimental Research on Abrasion Resistance and Predictive Model of High-Density Rubberized Concrete with High Strength. *Strength of Materials* 56: 842–852. <https://doi.org/10.1007/s11223-024-00695-9>.
24. Peng, Xi, Zhenxin Zhuang, and Qiuwei Yang. 2022. Predictive Modeling of Compressive Strength for Concrete at Super Early Age. *Materials* 15. <https://doi.org/10.3390/ma15144914>.
25. Asghar, Muhammad, Muhammad Faisal Javed, M Ijaz Khan, Sherzod Abdullaev, Fuad A Awwad, and Emad A A Ismail. 2023. Empirical models for compressive and tensile strength of basalt fiber reinforced concrete. *Scientific Reports* 13: 19909. <https://doi.org/10.1038/s41598-023-47330-2>.
26. Chidiac, Samir E, Fayez Moutassem, and Fathollah Mahmoodzadeh. 2013. Compressive strength model for concrete. *Magazine of Concrete Research* 65: 557–572. <https://doi.org/10.1680/mac.12.00167>.

27. Pukánszky, B. 1990. Influence of interface interaction on the ultimate tensile properties of polymer composites. *Composites* 21: 255–262. [https://doi.org/https://doi.org/10.1016/0010-4361\(90\)90240-W](https://doi.org/https://doi.org/10.1016/0010-4361(90)90240-W).
28. Horszczaruk, Elżbieta. 2008. Mathematical model of abrasive wear of high performance concrete. *Wear* 264: 113–118. <https://doi.org/https://doi.org/10.1016/j.wear.2006.12.008>.
29. Silva, Rui Vasco, Jorge de Brito, and Ravindra Kumar Dhir. 2016. Establishing a relationship between modulus of elasticity and compressive strength of recycled aggregate concrete. *Journal of Cleaner Production* 112: 2171–2186. <https://doi.org/https://doi.org/10.1016/j.jclepro.2015.10.064>.
30. Khasawneh, Mohammad Ali. 2025. Geopolymer concrete in construction projects: a review. *Discover Civil Engineering* 2: 124. <https://doi.org/10.1007/s44290-025-00281-1>.
31. Jedrzejko, M J, Y Gan, X Chen, H M Jonkers, and H Luo. 2025. Performance evaluation of EICP with organic/non-organic additives for repairing external cracks in cement-based materials. *Construction and Building Materials* 458: 139646. <https://doi.org/https://doi.org/10.1016/j.conbuildmat.2024.139646>.
32. Jedrzejko, M J, Y Gan, X Chen, H M Jonkers, and H Luo. 2025. Performance evaluation of EICP with organic/non-organic additives for repairing external cracks in cement-based materials. *Construction and Building Materials* 458: 139646. <https://doi.org/https://doi.org/10.1016/j.conbuildmat.2024.139646>.
33. Logakannan, Krishna Prasath, Ibrahim Guven, Gregory Odegard, Kan Wang, Chuck Zhang, Zhiyong Liang, and Ashley Spear. 2025. A review of artificial intelligence (AI)-based applications to nanocomposites. *Composites Part A: Applied Science and Manufacturing* 197: 109027. <https://doi.org/https://doi.org/10.1016/j.compositesa.2025.109027>.
34. EN 197-1. 2011. Cement - part 1: Composition, specifications and conformity criteria for common cements. Brussels.
35. BS EN 1097-6. 2013. Tests for mechanical and physical properties of aggregates: Determination of particle density and water absorption. London.
36. ASTM C1437. 2020. Standard test method for flow of hydraulic cement mortar. Pennsylvania.
37. BS EN 12390-3. 2019. Testing hardened concrete - Part 3: Compressive strength of test specimens. London.
38. ASTM C348. 2021. Standard test method for flexural strength of hydraulic-cement mortars. Pennsylvania.
39. EN 14157. 2017. Natural stone test methods - Determination of the abrasion resistance. Brussels.

40. Strzałkowski, Paweł, Urszula Kaźmierczak, and Michał Wolny. 2020. Assessment of the method for abrasion resistance determination of sandstones on Böhme abrasion test apparatus. *Bulletin of Engineering Geology and the Environment* 79: 4947–4956. <https://doi.org/10.1007/s10064-020-01868-x>.
41. Tseng, Yun-Sheng, Chen-Lin Huang, and Kung-Chung Hsu. 2005. The pozzolanic activity of a calcined waste FCC catalyst and its effect on the compressive strength of cementitious materials. *Cement and Concrete Research* 35: 782–787. <https://doi.org/https://doi.org/10.1016/j.cemconres.2004.04.026>.
42. Su, Nan, Hung-Yuan Fang, Zong-Huei Chen, and Fu-Shung Liu. 2000. Reuse of waste catalysts from petrochemical industries for cement substitution. *Cement and Concrete Research* 30: 1773–1783. [https://doi.org/https://doi.org/10.1016/S0008-8846\(00\)00401-4](https://doi.org/https://doi.org/10.1016/S0008-8846(00)00401-4).
43. Abdolpour, Hassan, Paweł Niewiadomski, Arkadiusz Kwiecień, Marcin Tekieli, and Łukasz Sadowski. 2023. Fundamental understanding of the mechanical and post- cracking behaviour of ultra-high performance mortar with recycled steel fibers. *Construction and Building Materials* 374: 130918. <https://doi.org/https://doi.org/10.1016/j.conbuildmat.2023.130918>.
44. García de Lomas, M, M I Sánchez de Rojas, and M Frías. 2007. Pozzolanic reaction of a spent fluid catalytic cracking catalyst in FCC-cement mortars. *Journal of Thermal Analysis and Calorimetry* 90: 443–447. <https://doi.org/10.1007/s10973-006-7921-7>.
45. Al-Jabri, Khalifa, Mahad Baawain, Ramzi Taha, Zahran Saif Al-Kamyani, Khalid Al-Shamsi, and Aysser Ishtieh. 2013. Potential use of FCC spent catalyst as partial replacement of cement or sand in cement mortars. *Construction and Building Materials* 39: 77–81. <https://doi.org/https://doi.org/10.1016/j.conbuildmat.2012.05.035>.
46. Nunes, Sandra, and Carla Costa. 2017. Numerical optimization of self-compacting mortar mixture containing spent equilibrium catalyst from oil refinery. *Journal of Cleaner Production* 158: 109–121. <https://doi.org/https://doi.org/10.1016/j.jclepro.2017.04.161>.
47. Roy, Tonmoy, Pobithra Das, Ravi Jagirdar, Mousa Shhabat, Md Shahriar Abdullah, Abul Kashem, and Raiyan Rahman. 2025. Prediction of mechanical properties of eco-friendly concrete using machine learning algorithms and partial dependence plot analysis. *Smart Construction and Sustainable Cities* 3: 2. <https://doi.org/10.1007/s44268-025-00048-8>.
48. Chen, Zheng, Jingwen Tang, Yichen Wang, Chaofan Yi, and Tao Su. 2025. Characterizing the interfacial bonding behaviour and influential mechanism of metakaolin-based geopolymer-concrete

- composites under shearing load: Experimental and modelling study. *Composite Structures* 369: 119336.
<https://doi.org/https://doi.org/10.1016/j.compstruct.2025.119336>.
49. Al-Jabri, Khalifa, Mahad Baawain, Ramzi Taha, Zahran Saif Al-Kamyani, Khalid Al-Shamsi, and Aysser Ishtieh. 2013. Potential use of FCC spent catalyst as partial replacement of cement or sand in cement mortars. *Construction and Building Materials* 39: 77–81.
<https://doi.org/https://doi.org/10.1016/j.conbuildmat.2012.05.035>.
 50. Jubori, Dawood S A, Abu B Nabilah, Nor A Safiee, Aidi H Alias, and Noor A M Nasir. 2024. Machine Learning Technique for the Prediction of Blended Concrete Compressive Strength. *KSCE Journal of Civil Engineering* 28: 817–835. <https://doi.org/https://doi.org/10.1007/s12205-024-0854-5>.
 51. Mohamed, Abdeliazim Mustafa, and Bassam A Tayeh. 2026. AI-driven computational methodologies of optimized mix design and performance prediction of ultra-high-performance concrete (UHPC): a systematic review. *Results in Engineering* 31: 111633.
<https://doi.org/https://doi.org/10.1016/j.rineng.2026.111633>.
 52. Abdolpour, Hassan, Murugan Muthu, Paweł Niewiadomski, Łukasz Sadowski, Łukasz Hojdys, Piotr Krajewski, and Arkadiusz Kwiecień. 2023. Performance and life cycle of ultra-high performance concrete mixes containing oil refinery waste catalyst and steel fibre recovered from scrap tyre. *Journal of Building Engineering* 79: 107890. <https://doi.org/https://doi.org/10.1016/j.jobbe.2023.107890>.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [2026WBVgraphicalabstract.docx](#)