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Data-Driven Selection of Concrete Modification Strategies: A Critical Review of Fibres, Polymers, Waste Materials and Machine-Learning Tools for Mechanical, Durability and Structural Performance

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Abstract: Concrete can now be modified in many ways, but engineers still lack a clear method for choosing between the options. Fibres, polymer admixtures, waste-derived materials and supplementary cementitious materials each act through a different mechanism, and each improves some properties while weakening others. This review treats modification as a selection problem rather than a list of additives. For each strategy it identifies the property it controls, the mechanism behind the effect, the main trade-off and the minimum evidence needed to support a performance claim. Mechanical, durability and structural performance are considered as separate selection criteria, because a mix that performs well in one may fail in another. The role of machine learning is then examined as a tool for screening and ranking candidate mixtures before testing. The literature shows that fibres mainly improve post-cracking behaviour and impact resistance, polymers improve adhesion and reduce permeability at some cost in compressive strength, and waste and supplementary materials reduce clinker demand but require longer curing and careful characterisation. Machine-learning models predict compressive strength well within their training range, but datasets for modified mixtures, durability and structural response remain small and poorly described. A five-step data-driven selection framework and a property–strategy matrix are proposed. The review concludes that machine learning is most useful for narrowing the choice of mixtures, while final selection must still rest on targeted experiments.

Keywords: Concrete modification; Fibre-reinforced concrete; Polymer-modified concrete; Waste materials; Machine learning; Durability; Mix selection

1. INTRODUCTION

Concrete is the most used construction material, and the clinker in Portland cement is responsible for most of its carbon footprint [1]. Partial replacement of clinker by supplementary cementitious materials (SCMs) is the most practical route to lower emissions [2]. These materials also change hydration, pore structure and long-term durability, so they cannot be treated as simple fillers [3].

At the same time, concrete is expected to do more than carry compressive load. Designers ask for crack control, toughness, impact resistance, low permeability and a long service life. Fibres, polymer admixtures, bacterial agents and waste-derived materials have each been proposed to meet these needs. Recent reviews have examined them as modification strategies [4] and in terms of durability [5].

The difficulty is that these strategies are rarely compared on the same basis. A fibre that improves toughness may reduce workability, and a polymer that lowers permeability may reduce compressive strength. A waste powder that saves cement may slow early strength gain. The best choice therefore depends on which property governs the design, and on what can be traded away.

Machine learning (ML) offers a way to handle this complexity. Models trained on mixture data can predict strength faster than trial batching [6], and hybrid models can outperform empirical equations for cement-based materials [7]. Optimisation methods can then search for mixtures that balance strength, cost and carbon [8]. Data-driven tools are also being applied to structural response under extreme loading [9].

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Most studies, however, use ML to predict a single property of a known mix. Few ask how ML can help engineers *select* a modification strategy for a given requirement. This review addresses that gap. Its objectives are to:

1. Summarise the mechanisms by which fibres, polymers and waste materials change concrete behaviour.
2. Identify the trade-offs and the evidence needed for mechanical, durability and structural claims.
3. Assess where ML can support selection, and where its use is not yet reliable.
4. Propose a practical selection framework linking performance requirements to strategies, tests and models.

2. REVIEW APPROACH

This is a critical narrative review, not a systematic review or meta-analysis. Journal articles and reviews were identified in Google Scholar and Scopus-indexed journals. Search terms combined fibre-reinforced concrete, polymer-modified concrete, waste marble, recycled aggregate, fly ash, slag, durability, freeze–thaw, blast, machine learning, neural network, random forest and SHAP.

Studies were selected if they explained a mechanism, reported a defined test or reviewed a part of the field clearly. Only sources with complete and verifiable bibliographic details and a digital object identifier (DOI) were retained. Because mixtures, specimen sizes and test standards differ widely, results are compared qualitatively rather than pooled.

3. FIBRES

3.1 Mechanism and governing property

Fibres do little before the matrix cracks. Once a crack opens, fibres crossing it carry tensile stress and dissipate energy by debonding and pull-out [10]. This turns sudden brittle failure into gradual failure. The main benefits are therefore flexural toughness, residual strength, crack-width control and impact resistance, while compressive strength changes little [11].

Fibre type sets the range of action. Short microfibres mainly limit plastic shrinkage cracking. Macrofibres and steel fibres provide residual load capacity after cracking [10, 11]. Natural fibres have low embodied energy but need protection from the alkaline matrix [11].

3.2 Polypropylene fibres

Polypropylene (PP) fibres are light, inert, corrosion-free and cheap. A systematic review found that low to moderate PP dosages improve splitting tensile and flexural strength and crack resistance, while high dosages reduce workability and dispersion [12]. PP fibres also improve resistance to shrinkage cracking and some durability indicators [13]. Their low modulus, however, limits their effect to small crack openings.

3.3 Impact and selection implications

Under impact, fibres reduce spalling and scabbing and increase the number of blows to failure [14]. Results are hard to compare because drop-weight, projectile and split-Hopkinson-bar tests impose different strain rates [15]. Ultra-high-performance fibre-reinforced concrete (UHPFRC) shows much smaller deflections than normal concrete under impact and blast [16].

For selection, fibres are the first choice when toughness, crack width or impact governs. They are a poor choice when compressive strength alone governs. A fibre mix should always be tested in flexure or impact, never judged by cube strength [4].

4. POLYMERS

4.1 Mechanism

Polymer admixtures such as styrene–butadiene rubber, acrylic emulsions, epoxies and polyvinyl acetate (PVAc) form films within the hydrating paste. Ohama described the result as a co-matrix in which cement hydration and film formation proceed together [17]. The films bridge microcracks, seal part of the capillary pores and improve bond to aggregates and old substrates.

4.2 Effects and trade-offs

Aggarwal et al. found that epoxy and acrylic emulsions improved the flexural strength, bond and water resistance of mortars, with the effect depending on polymer–cement ratio and curing [18]. Compressive strength and modulus usually fall slightly, because polymers entrain air, retard hydration and need dry curing to form films. Fowler noted that polymer concretes remain niche products mainly because of cost and a lack of design guidance [19].

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Low-cost PVAc adhesives are sometimes added on site. Kudoli tested Fevicol, a PVAc-based adhesive, in concrete and reported its effect on workability and strength at different dosages [20]. PVAc is, however, sensitive to moisture and alkaline hydrolysis, so results for one trade product cannot be generalised to all polymers.

4.3 Selection implications

Polymers are the logical choice where adhesion, flexibility or low permeability governs: repair mortars, thin overlays, bonding layers and precast units in aggressive exposure. They are not suited to mass structural concrete where compressive strength and cost dominate. Any polymer study used for selection should report the polymer chemistry and solids content, not only the trade name.

5. WASTE AND SUPPLEMENTARY MATERIALS

5.1 Fly ash and slag

Fly ash and ground granulated blast-furnace slag (GGBS) are the most widely used SCMs. High-volume Class F fly ash concrete has lower 28-day strength but gains strength substantially up to one year [21]. GGBS is latent hydraulic, so it gains strength faster than fly ash and refines pore structure in the long term [22]. The reactivity of fly ash depends on its glass content, fineness and unburnt carbon [23].

For selection, the key trade-off is time. Both materials reduce clinker and improve chloride and sulphate resistance, but they need longer moist curing and should be judged at later ages [2, 3].

5.2 Waste marble and recycled aggregate

Waste marble can replace either cement or fine aggregate, and the two routes behave differently. Aliabdo et al. found that marble dust can replace sand without a large loss of strength, whereas cement replacement was less effective because it diluted the binder [24]. A recent review identified replacement level, fineness and composition as the main controls on performance [25]. Sathe et al. tested both routes and reported mechanical, durability and microstructural results [26].

Recycled concrete aggregate carries adhered mortar, which raises water absorption and lowers density and strength [27]. The performance of recycled waste materials depends strongly on processing, replacement ratio and mix adjustments such as pre-saturation [28].

5.3 Selection implications

Waste and supplementary materials are chosen mainly for resource and carbon efficiency. The largest carbon saving comes from replacing clinker with a reactive material, not from inert fillers [1]. A selection study must therefore state the replacement basis (binder or aggregate), the source and the full characterisation: particle size, specific gravity, absorption and chemical composition [28].

6. DURABILITY AS A SELECTION CRITERION

6.1 Why strength is not enough

Durability is governed by transport of water and ions, cracking, frost and chemical attack, not by compressive strength. Basheer et al. showed that permeation properties such as absorption, permeability and diffusion are the most useful general indicators of durability [29]. A modification should therefore be selected for durability only on the basis of tests that measure the relevant mechanism [5].

6.2 Freeze–thaw resistance

Freeze–thaw damage develops as internal microcracking and surface scaling [30]. Li et al. showed that damage stays small until the degree of saturation passes a critical value, after which it rises quickly [31]. Air entrainment, a low water–cement ratio and suitable SCMs are the main design levers; dense matrices are not frost-resistant without an adequate air-void system [32]. Fibres can limit crack growth during freezing but do not replace entrained air.

6.3 Self-healing as an added function

Bacterial agents can be combined with other strategies to seal fine cracks. Jonkers et al. showed that bacterial spores survive in concrete and precipitate calcite in cracks [33]. Wiktor and Jonkers sealed cracks up to about 0.46 mm wide and made them watertight [34]. A wider review concluded that the best healing mechanism depends on crack width, moisture and the speed of healing needed [35]. Crack sealing restores water-tightness but recovers little load capacity.

6.4 Selection implications

For durability-governed design, the selection must start from the exposure class. Fibres suit cracked members, polymers suit transport-controlled exposure, and SCMs suit chloride and sulphate exposure if curing is adequate. Experimental

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freeze–thaw testing combined with ML prediction shows that models can shorten long durability campaigns, but only with consistent damage definitions [36].

7. STRUCTURAL PERFORMANCE UNDER EXTREME LOADING

Blast and impact loads rise in microseconds, so structural response depends on inertia, strain-rate effects and local breach as much as on strength [37]. Explicit-dynamics analysis of reinforced concrete (RC) frames has shown how stand-off distance, charge weight and angle of incidence govern displacement and damage [38]. Robustness depends on redundancy, ductility and continuity, so that loss of one member does not trigger disproportionate collapse [39].

Fibre-reinforced and UHPFRC materials reduce spalling and increase energy absorption [16]. However, material-level gains do not automatically give structural resilience. Taware and Kudoli argued that such gains must be confirmed at member and system level, and proposed a staged resilience framework from resistance to recovery [9].

ML surrogates can predict member response quickly once trained on test or simulation data. Almustafa and Nehdi developed an ML model that predicts the response of RC slabs under blast [40]. Such surrogates inherit every assumption of the simulations used to train them, so they must not be used outside their training range.

For selection, structural claims require a hierarchy of evidence: material tests at the relevant strain rate, then member tests or validated simulations, then system-level checks.

8. MACHINE-LEARNING TOOLS FOR SELECTION

8.1 Strength prediction

Yeh showed early that artificial neural networks predict the strength of concrete containing fly ash and slag better than regression [41]. Chou et al. compared data-mining methods and found that an ensemble of regression trees gave the best accuracy among those tested [42]. Later reviews confirmed that ensembles and neural networks usually outperform single models [6, 43]. Kudoli and Bala reported similar findings for cement and cement mortar, where hybrid models gave excellent accuracy [7].

High accuracy has limits. Young et al. showed, with a large industrial dataset, that mixture proportions alone cannot capture batch-to-batch variation in materials and testing [44]. High accuracy on a benchmark therefore reflects good interpolation, not universal predictive power.

8.2 Modified mixtures, durability and structure

Models for modified mixtures need descriptors that most datasets lack: fibre geometry, polymer chemistry, replacement basis and waste characterisation. Doke and Kudoli concluded that ML works best as a screening tool when supported by grouped validation, uncertainty reporting and experimental confirmation [45]. Durability prediction is harder still, because exposure data are scarce and test methods vary [46].

8.3 Validation and interpretability

Random train–test splits overestimate accuracy when repeated specimens of one mix appear in both sets. Roberts et al. showed that grouped or blocked cross-validation gives more honest error estimates for such data [47]. SHAP values help check that a model has learned sensible trends, such as strength rising with age [48]. Rudin argued that interpretable models should be preferred for high-stakes decisions when they perform comparably [49]. Physics-informed learning can also keep predictions within physical limits outside dense data [50].

8.4 From prediction to selection

Once a reliable model exists, optimisation can search for mixtures that meet strength, cost and carbon targets together [8]. For selection, the model's role is to rank candidates and remove weak options, not to replace testing. Its domain of applicability must be stated, so that it is not used for materials or exposures it has never seen.

9. A DATA-DRIVEN SELECTION FRAMEWORK

Selection should start from the governing performance requirement, not from the additive. Table 1 links each requirement to the most suitable strategy, the main trade-off and the minimum evidence needed.

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Table 1. Property–strategy matrix for selecting concrete modifications

Governing requirement	Preferred strategy	Main trade-off	Minimum evidence	Key refs
Crack control and toughness	PP, steel or hybrid fibres	Lower workability, dispersion	Flexural toughness, residual strength, crack width	[10–13]
Impact or blast resistance	Steel fibres, UHPFRC	Cost, mixing difficulty	Impact tests at relevant strain rate, member check	[9, 14–16]
Adhesion and repair bond	Polymer admixtures	Slight loss of compressive strength	Bond and flexural strength, sorptivity	[17–20]
Low carbon and resource use	Fly ash, GGBS, waste marble	Slower early strength, source variability	Strength at 28 and 90 days, characterisation	[21–28]
Chloride and sulphate resistance	SCMs with adequate curing	Curing sensitivity	Chloride penetration, sulphate expansion	[2, 3, 29]
Frost resistance	Air entrainment plus SCMs or fibres	Strength reduction from air	Air-void parameters, freeze–thaw cycling	[30–32]
Sealing of fine cracks	Bacterial agents	Bacterial survival, retarded hydration	Permeability recovery, repeated healing	[33–35]

The matrix is applied in five steps:

1. **Define the requirement.** Identify the governing property and the exposure class, including any extreme-loading scenario.
2. **Shortlist strategies.** Use Table 1 to select one or two candidate strategies and note their trade-offs.
3. **Screen with ML.** Use a validated model, within its stated domain, to rank candidate mixtures and discard weak options.
4. **Test the shortlist.** Run the minimum evidence tests in Table 1 against a matched control with the same water–binder ratio, curing and age.
5. **Feed back the data.** Add the new results, with full material descriptors, to the dataset so that the model improves over time.

This loop makes ML a decision-support tool rather than a final answer. It also produces datasets with the material and exposure detail that current models lack.

10. RESEARCH GAPS AND CONCLUSIONS

10.1 Research gaps

1. Few studies report a balanced profile of fresh, mechanical, durability and dynamic properties for the same mixture.
2. Open datasets rarely include fibre geometry, polymer chemistry, replacement basis or waste characterisation.
3. Impact and freeze–thaw tests are not standardised enough for results to be pooled.
4. Hybrid systems combining fibres, polymers, SCMs and bacteria are seldom studied with factorial designs.
5. ML models are seldom validated on grouped splits or confirmed by new experiments.

10.2 Conclusions

1. No single modification improves every property. Selection must begin with the governing requirement and accept a known trade-off.
2. Fibres act after cracking and are the best choice for toughness, crack control and impact; they change compressive strength little.
3. Polymers improve adhesion and lower permeability at a small cost in compressive strength, and suit repair and overlays.

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4. Fly ash, GGBS and waste materials reduce clinker demand but need longer curing, later-age testing and full characterisation.
5. Durability and structural claims need mechanism-specific tests; strength results alone cannot support them.
6. ML predicts strength well within its training range and is most useful for screening and ranking candidate mixtures.
7. The proposed matrix and five-step framework link requirements, strategies, tests and models, and turn each project into new data for better selection.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Rohan Bhondve: Investigation, Data curation, Visualization, Writing – original draft. **Anand B. Kudoli:** Conceptualization, Methodology, Supervision, Validation, Writing – review and editing.

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