

Review

Artificial Intelligence Readiness of Bacterial Self-Healing Cement-Based Materials: Evidence, Design Constraints, and Research Priorities

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Abstract

Bacterial self-healing cement-based materials (BSHCMs) couple microbial mineralization with cement-based material design to autonomously seal cracks and potentially restore durability. However, their performance depends on a complex interaction among bacterial viability and physiological state, mineralization pathway, carrier and nutrient systems, calcium availability, matrix chemistry, crack characteristics, moisture, and exposure history. This review, supported by bibliometric mapping of 805 Scopus-indexed records, examines these interdependencies through the specific lens of artificial intelligence (AI) readiness. The mapping revealed six interconnected research themes spanning bacterial mineralization, sustainable cement-based systems, matrix chemistry and transport, encapsulation, durability, and machine learning (ML). AI evidence was classified as directly demonstrated in bacterial self-healing systems, transferable from adjacent concrete and structural health monitoring applications, or prospective. Although existing ML studies report high internal predictive performance, their engineering generalizability remains limited by heterogeneous and frequently literature-derived datasets, random train–test partitioning, potential feature leakage, synthetic data dependence, insufficient uncertainty reporting, and scarce independent laboratory or field validation. The analysis further shows that sustainability and economic benefits cannot be assumed from the biological nature of the technology but must be demonstrated through service life extension relative to the additional burdens of cultivation, nutrients, carriers, and processing. Advancing BSHCMs toward trustworthy AI-supported engineering, therefore, requires harmonized and machine-readable datasets, matched attribution controls, delayed cracking and realistic exposure experiments, explicit uncertainty and negative result reporting, study-grouped and external validation, and pilot- to field-scale testing. AI should consequently be regarded not as a substitute for biological healing, but as a decision support layer whose value depends fundamentally on the quality, traceability, and transferability of the underlying experimental evidence.

Keywords: bacterial self-healing concrete; biomineralization; microbially induced calcium carbonate precipitation; artificial intelligence readiness; machine learning validation; data provenance; external validation; functional recovery; experimental standardization; service life extension



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1. Introduction

Cement-based composites remain fundamental to modern infrastructure because of their mechanical properties, availability, versatility, and economic feasibility. However, cracking represents a major durability issue in reinforced concrete. Even microcracks can create preferential pathways for water, oxygen, chlorides, sulfates, carbon dioxide (CO₂), and other aggressive agents, accelerating reinforcement corrosion, matrix degradation, permeability increase, and loss of serviceability [1–3]. Therefore, strategies that reduce crack propagation, restore watertightness, and delay deterioration are increasingly important for extending the service life of concrete infrastructure. Self-healing cement-based materials have been proposed as one approach to improve durability and reduce maintenance demand. In conventional cement-based systems, autogenous healing may occur through continued hydration of unreacted cement particles, swelling of hydration products, and abiotic calcium carbonate precipitation within narrow cracks [4]. This process is usually limited to small crack widths and depends strongly on water availability, crack age, binder composition, and exposure conditions [5,6]. Bacterial self-healing extends this concept by incorporating dormant spores or protected vegetative cells that can become activated after crack formation and water ingress and promote calcium carbonate precipitation within the crack [1,7,8]. The main mechanism behind bacterial self-healing is microbiologically induced calcium carbonate precipitation. Under suitable conditions, bacterial metabolism can increase carbonate availability, modify local alkalinity, or accelerate carbonate speciation, allowing carbonate ions to react with calcium ions and form calcium carbonate (CaCO₃) deposits [9–11]. These mineral precipitates may partially or completely fill cracks, reduce permeability, limit capillary absorption, and slow the ingress of aggressive substances. However, bacterial self-healing should not be viewed as a simple additive-based repair strategy. It is a bioengineered mineralizing process that requires compatibility between bacterial physiology, carrier design, nutrient availability, moisture transport, crack geometry, and exposure conditions [7,12,13].

The practical implementation of bacterial self-healing cement-based materials (BSHCM) is still limited by several biological and engineering constraints. Fresh cement paste is characterized by high alkalinity, ionic stress, hydration heat, pore refinement, and limited availability of water, oxygen, and nutrients, which can strongly reduce bacterial viability [12,14,15]. For this reason, most systems rely on alkali-tolerant, spore-forming microorganisms, particularly *Bacillus*-related species, together with protective carriers or encapsulation systems [16]. Expanded clay, expanded perlite, silica gel, polyurethane, alginate beads, hydrogels, microcapsules, coated particles, and air-entrained voids have been investigated as protective microenvironments for bacterial cells or spores [4,13,17–24]. Nevertheless, these systems may also affect workability, porosity, mechanical properties, transport properties, cost, and scalability. Thus, bacterial self-healing requires a balance between biological protection and cement-based material performance. Performance evaluation should also move beyond visual crack closure. Surface sealing can be misleading if internal transport pathways remain open or if the deposited material does not restore the durability of the cement-based composite. More relevant indicators include water permeability, capillary absorption, chloride ingress, corrosion delay, mineral distribution inside the crack, CaCO₃ polymorph identification, bacterial viability, and partial recovery of mechanical properties [5,13,24–26]. These indicators are necessary to distinguish true bio-mediated healing from autogenous healing, superficial mineral deposition, or temporary crack filling. From a sustainability perspective, the main potential value of bacterial self-healing technology lies in service life extension and reduced maintenance demand. If autonomous crack sealing can delay water and chloride ingress, reduce repair frequency, and prevent premature deterioration, it may contribute to lower lifecycle impacts of con-

crete infrastructure [27]. However, sustainability should not be assumed solely because microorganisms are used. Bacterial cultivation, carriers, nutrients, encapsulation materials, and additional processing steps also have environmental and economic burdens [28].

Artificial intelligence (AI) has recently been introduced as a tool for prediction, optimization, crack image analysis, sensing, and decision-making in self-healing cement-based systems. Machine learning (ML) models can help predict healing performance from variables such as bacterial type, carrier system, nutrient chemistry, crack width, curing regime, water to binder ratio, and exposure conditions [29–31]. Deep learning can assist in crack detection and segmentation, while sensor-based models may support monitoring of humidity, resistivity, acoustic emission, temperature, and healing progress [32,33]. Nevertheless, the role of AI must be interpreted realistically. AI cannot replace bacterial CaCO_3 precipitation, maintain bacterial viability, supply nutrients, etc. Its value is primarily supportive since it can help identify influential variables, reduce experimental trial and error, rank promising formulations, and support predictive monitoring [29,30,33]. Despite substantial progress, the field still lacks harmonized experimental protocols and machine-readable datasets. Published studies differ widely in bacterial strain, cell or spore concentration, carrier type, nutrient source, mix design, crack induction method, crack width, crack age, healing regime, and evaluation metrics. This heterogeneity complicates comparison among studies and limits the reliability of AI-based models trained on literature data [15,30,34]. Recent reviews have summarized bacterial healing mechanisms, microbial viability, encapsulation strategies, mechanical and durability performance, and broader data-driven trends in BSHCMs [1,15]. The distinct purpose of the present review is, therefore, to evaluate BSHCMs through an AI-readiness lens: which biological and material variables must be measured before data-driven models become meaningful; which AI claims are supported by direct BSHCM evidence; which methods are transferable from adjacent fields; and which applications remain prospective. In addition, the review examines how validation strategy, uncertainty, attribution controls, and domain shift affect the credibility of reported model performance and proposes minimum experimental and reporting requirements for reusable, field-relevant datasets.

Scope of the Review and Supporting Literature Mapping

This article is a structured critical review supported by bibliometric mapping. This part of the search was focused on peer-reviewed research articles published in English between 2020 and 2025 and was designed around three thematic blocks: microbial and bacterial self-healing, cement-based materials or concrete, and AI or ML. The complete search string, database limits, inclusion criteria, and exclusion criteria are provided in Supplementary Table S1. Additional methodological details on data export, keyword processing, and co-occurrence mapping and explanations of total link strength are presented in Supplementary Text S1. The co-occurrence analysis was performed using VOSviewer software, version 1.6.20, based on author keywords and index keywords exported from Scopus. The obtained full network visualization is provided in Figure 1, while keyword occurrences, total link strengths, cluster assignments, average publication years, and related indicators are summarized in Supplementary Table S2. In brief, 805 records were identified and subsequently screened based on their titles and abstracts. No records were excluded during the screening stage, resulting in a final corpus of 805 records covering the period 2020–2025. Among the 139,462 terms identified in the corpus, 6339 met this threshold and were included in the co-occurrence analysis. Furthermore, the co-occurrence analysis revealed a highly interconnected network of terms, comprising 53,532 co-occurrence links with a cumulative total link strength of 273,886 and 14,339 term occurrences. These values indicate extensive and relatively strong associations among the terms represented in the an-

The second cluster was associated with sustainable cement-based materials and circular resource use, including supplementary cement-based materials, waste-derived resources, fly ash, silica fume, lifecycle assessment, environmental impact, and carbon emissions. This cluster justifies the inclusion of sustainability limits and service life extension as a distinct part of the review. A third cluster was related to cement hydration, microstructure, and transport processes, including hydration products, slag, geopolymer systems, carbonation, C-S-H formation, ion transport, and microstructural characterization. This cluster highlights the importance of cement chemistry and matrix compatibility in determining whether bacterial mineralization can become functionally relevant. A fourth cluster focused on encapsulation and autonomous healing technologies, including microcapsules, capsules, healing agents, superabsorbent polymers, recovery, and healing efficiency. The fifth cluster reflected durability and service condition performance, with terms related to marine exposure, moisture, electrical resistivity, bacterial mineralization, hydrogel systems, and long-term behavior. This cluster emphasizes that bacterial healing must be assessed beyond laboratory crack closure and should include transport recovery, durability indicators, and service life relevance. Finally, a distinct ML cluster included model, prediction, ML, artificial neural networks (ANNs), random forest, XGBoost, support vector machines, and accuracy-related metrics. This cluster confirms that AI is increasingly connected to material prediction, optimization, and monitoring, but it also supports the position taken in this review that AI should be treated as a decision support tool rather than as a replacement for biological or materials engineering solutions [35]. Collectively, these six clusters informed the organization of the subsequent critical synthesis into biological pathways and design variables, carrier and material constraints, sustainability and technology trade-offs, AI evidence maturity, and future validation priorities.

2. Biological Basis and AI-Relevant Design Variables

As can be seen on conceptual framework (Figure 2), BSHCMs are bioengineered mineralizing systems in which bacterial physiology, the cement-based matrix, protective carriers, nutrients, calcium availability, water ingress, and crack geometry interact [36–38].

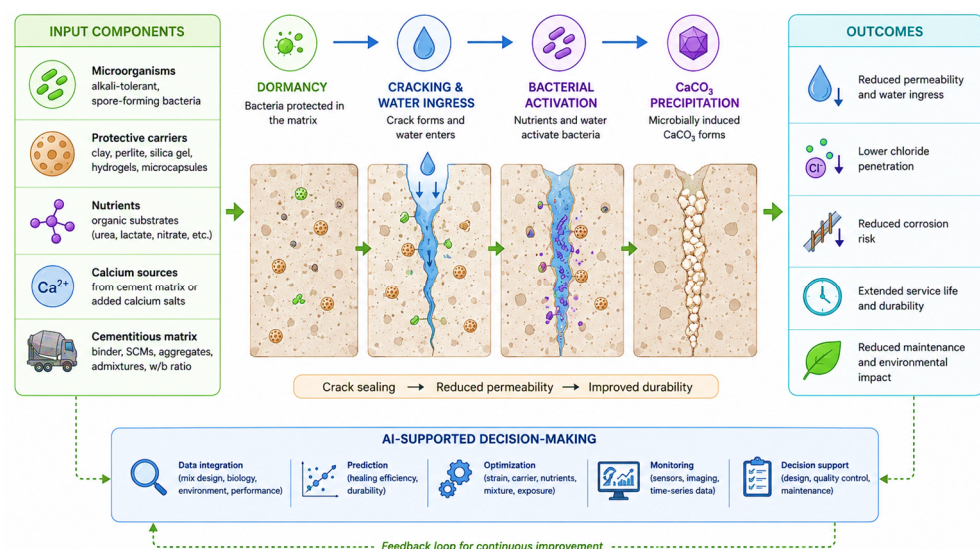


Figure 2. Conceptual framework of bacterial self-healing cement-based materials synthesized from the reviewed literature; the scheme does not represent a single experimentally validated workflow (BioRender was used for the preparation and graphical refinement of scientific illustrations).

Crack formation changes the local transport environment and can reactivate protected cells or spores, allowing bacterial metabolism to increase carbonate availability or alkalinity

and support CaCO_3 precipitation [39–45]. The response is conditional rather than automatic: viability, substrate access, moisture, pH, calcium supply, and time for nucleation and growth must coincide at the crack [46–48]. These dependencies are also the principal candidate variables for data-driven prediction. The cement-based matrix imposes high alkalinity, ionic stress, hydration heat, and progressive pore refinement, all of which can reduce bacterial survival and later activation [12,14–16]. Spore-forming, alkali-tolerant *Bacillus*- and *Sporosarcina*-related organisms are, therefore, frequently used, often with carriers or encapsulation to provide physical protection, moisture storage, and co-delivery of nutrients [11,16–24]. Recent work with *Bacillus licheniformis* further suggests that the self-healing potential of a selected bacterial strain should not necessarily be regarded as a fixed property but may be influenced by its physiological state and adaptation to the intended application conditions [49]. Recent strain adaptation studies further indicate that enhanced saline–alkali tolerance may improve the suitability of *Sporosarcina pasteurii* for concrete crack repair environments [50]. However, protection is not neutral since carrier dosage can alter workability, porosity, strength, and transport properties. AI-ready experiments must, therefore, record both biological survival and the material consequences of the protection strategy rather than optimizing one in isolation. For predictive modeling, bacterial identity alone is an insufficient descriptor. Mechanistically meaningful inputs include viability or spore state, pathway activity, carrier properties and dosage, nutrient and calcium chemistry, crack width and age, moisture regime, temperature, water to binder ratio, and exposure history. AI can help rank and combine these variables, but it cannot compensate for an experimentally non-viable biological system [29,30,51,52].

Several bacterial pathways can support CaCO_3 precipitation, but their suitability for embedded cement-based systems differs in substrate demand, redox requirements, by-products, kinetics, and evidence maturity [53–56]. Table 1 summarizes the principal trade-offs among these pathways and highlights the mechanistically relevant variables that should be retained in future machine-readable datasets. Ureolysis remains the best-established route because it produces carbonate rapidly and has been evaluated extensively in bacterial BSHCM, but ammonia/ammonium generation is an environmental and process-design disadvantage [9–11,53].

Table 1. Comparison of bacterial mineralization pathways relevant to BSHCM and data-driven modeling.

Pathway	Principal Advantage	Limitation	AI-Relevant Variables
Ureolysis	Rapid alkalization and CaCO_3 precipitation; mature laboratory evidence	Ammonium/ammonia burden; strong dependence on substrate supply and urease activity	Urease activity, urea/Ca dose, pH, temperature, viability, crack moisture
Denitrification	Can function under low- O_2 conditions and avoids ureolytic ammonia	Redox control; nitrate/nitrite/ NO_x management; pathway complexity	Nitrate, redox state, electron donor, pH, moisture, culture state
Organotrophic mineralization	Non-ureolytic route compatible with spore-based systems	Transport of organic substrate; moisture/ O_2 dependence; potentially slower activation	Carbon source, wet–dry regime, crack width, dormancy, nutrient depletion
Carbonic anhydrase-assisted	Can accelerate carbonate chemistry without ureolysis	Activity retention in cement-based environments; less mature field evidence	Enzyme/activity indicator, pH, $\text{CO}_2/\text{HCO}_3^-$, carrier, calcium availability

Denitrification, organotrophic mineralization, and carbonic anhydrase-assisted routes avoid direct ureolytic ammonia and may offer application-specific advantages, yet their activation requirements and long-term evidence are less mature [25,26,57–60]. These pathways should, therefore, not be ranked by crack closure alone; comparative studies should also quantify viability, reaction products, by-products, transport recovery, and delayed cracking performance.

3. Design Constraints, Sustainability, and Technology Trade-Offs

The practical performance of BSHCM is governed by coupled design constraints (Figure 3): survival during mixing and curing, protection during dormancy, nutrient and calcium retention, crack-triggered water access, matrix compatibility, and long-term exposure [61–65]. A strain that precipitates CaCO_3 efficiently in culture may still fail in BSHCMs if any one of these links is lost.

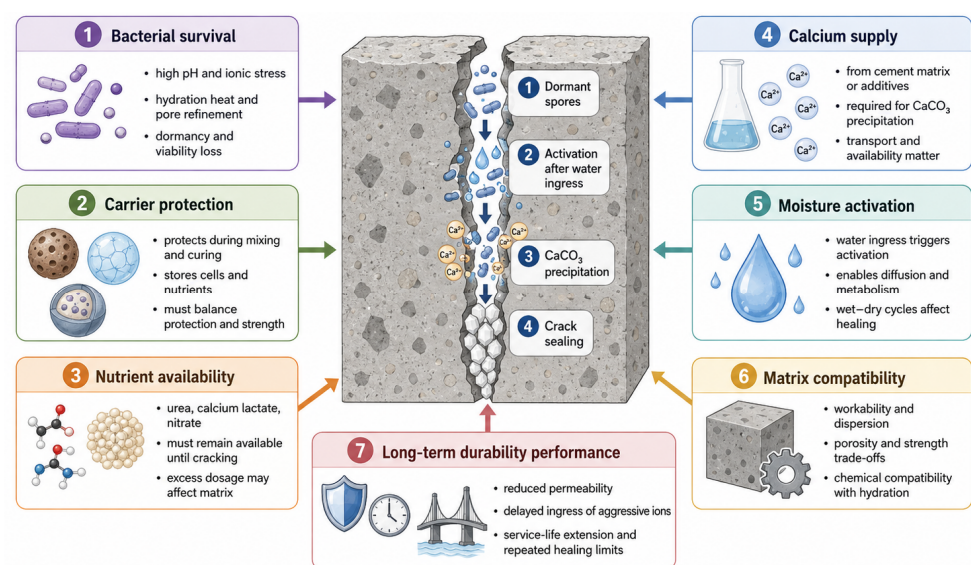


Figure 3. Main design constraints controlling bacterial self-healing in cement-based materials, including bacterial survival, carrier protection, nutrient availability, calcium supply, moisture activation, matrix compatibility, and long-term durability performance (BioRender was used for the preparation and graphical refinement of scientific illustrations).

Consequently, experimental design should treat healing as a multi-objective problem rather than maximizing surface crack closure alone. Long-term survival is a central biological constraint. Directly incorporated cells or spores can lose viability as hydration proceeds and pore space becomes less accessible, whereas porous carriers and protective matrices can extend survival and improve access to water and substrates [4,17,66]. However, bacterial contribution must be separated from autogenous and carrier-mediated effects. Visual closure is, therefore, insufficient by itself; permeability recovery, chloride transport, mechanical recovery where claimed, mineral distribution, and viable cell or activity measurements provide a more defensible assessment [5,13,24–26]. Carrier strategies include porous lightweight aggregates, expanded perlite or clay, silica gel, polyurethane, alginate beads or hydrogels, microcapsules, coated particles, and air-entrained voids (Figure 4) [8,13,17–24]. Their common purpose is to reduce direct biological exposure to the cement-based environment and improve access to water and nutrients after cracking. Because carrier chemistry, particle size, porosity, absorption, loading, and rupture/release behavior also influence the host matrix, these parameters should be reported as model inputs rather than treated as background details. Activation is usually both crack-triggered

and water-triggered. Hydrogels may retain water, while porous aggregates can act as local reservoirs and microcapsules can provide triggered release. These mechanisms can improve biological activation, but they can also change porosity, diffusion, and mechanical performance. The central design criterion is, therefore, a balance between protection and matrix integrity, as summarized in Table 2 [13,25,26].

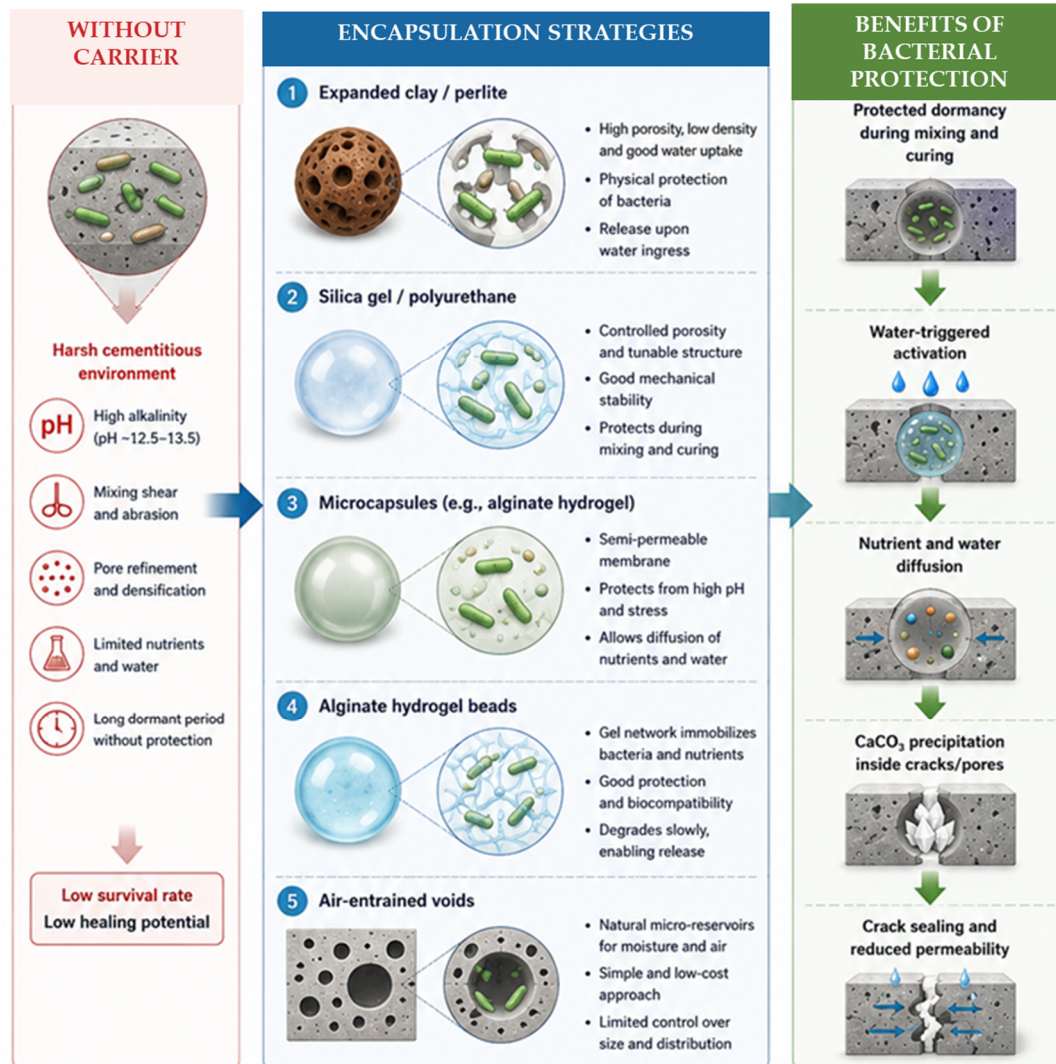


Figure 4. Encapsulation in self-healing cement-based systems (BioRender was used for the preparation and graphical refinement of scientific illustrations).

Carrier selection should be treated as a trade-off between biological protection, transport access, mechanical compatibility, processing robustness, and cost rather than as a simple ranking by cell survival. Table 2 summarizes the main design variables that should be reported consistently. A general framework for the self-healing process is, therefore, select a viable mineralization pathway; select direct incorporation or a compatible protection system; define nutrient and calcium delivery; introduce controlled cracking and water exposure; quantify biological activation and mineral formation; and evaluate both crack sealing and functional recovery. This sequence also defines the minimum causal chain that AI models should respect.

Table 2. Carrier/protection trade-offs and minimum reporting variables for BSHCM.

Carrier/Protection Concept	Biological Benefit for BSHCM	Risk for BSHCM	Key Reporting Variables
Lightweight porous aggregates (expanded clay, perlite, ACG, etc.)	Physical protection; moisture and nutrient reservoir	Porosity/strength penalty, variable loading, mixing damage	Particle size, porosity, absorption, bacterial/nutrient loading, dosage
Alginate beads/hydrogels	Cell protection and water retention; controlled swelling/release	Strength loss at high dose; diffusion limitations; capsule integrity	Polymer composition, crosslinking, bead size, swelling, viability before/after curing
Microcapsules/coated particles	Isolation during mixing and triggered release after cracking	Premature rupture, shell thickness, cost, mostly single-use activation	Capsule diameter, shell material, rupture behavior, loading, survival rate
Air-entrained void protection	Simple industrial route; potentially lower cost	Strong dependence on AEA chemistry and air content	AEA type, total air, spore dose, crack age, healing environment

The potential sustainability benefit of BSHCM lies primarily in extending service life and reducing maintenance rather than in the biological origin of the healing agent [51]. Service life-oriented analyses further indicate that the environmental value of self-healing should also be assessed at the structural level, where improved durability may translate into avoided repair, replacement, or additional material demand [67]. Functional performance must, therefore, be demonstrated through durable reductions in transport or deterioration risk, not only surface closure. Reported improvements vary strongly with bacterial strain, carrier, crack geometry, age at cracking, and exposure, so pooled percentages should not be generalized across incompatible protocols. Sustainability claims should use the same caution: biological cultivation, nutrients, carriers, and encapsulation all add burdens that must be offset by avoided repair or structural redesign. Sustainability claims should be separated into material-level burden and structure-level benefit. In the lifecycle assessment by Justo-Reinoso et al. [27], 1 m³ of a non-ureolytic BSHCM containing spores encapsulated in porous calcium–silicate granules showed an overall environmental impact approximately 85% higher than the conventional reference, together with a 36% larger embodied carbon footprint and a 51% larger water footprint. However, selective structural use that allowed wider crack limits and reduced non-structural crack control reinforcement produced scenario-dependent sustainability improvements of approximately 12–50%, depending on the impact category [27]. This example demonstrates why “bio-based” should not be used as a proxy for “low-impact”: the outcome depends on the healing agent, functional unit, service life benefit, avoided repair, and structural redesign. BSHCM nevertheless remains limited by biological persistence, delayed activation, nutrient depletion, and repeated healing capacity. Viability can decline substantially with curing time and temperature, and favorable early-age results do not establish that a system will reactivate after months or years of dormancy [12,14]. Repeat healing is also uncertain when cells, nutrients, or carrier contents are exhausted. Future studies should, therefore, include delayed cracking designs and report viability or activity at the time of cracking rather than only before incorporation. The cost of BSHCM is similarly system-specific. Da Silva et al. reported an operational expense of approximately EUR 500 per kg of bio-agent for an axenic ureolytic spore production route and developed a non-axenic alternative with operating expenses approximately 40 times lower, although spore production remained costly [68]. In a different protection strategy, it found that a suitable commercial air-entraining admixture for directly added spores was approximately 13 times less expensive than protection with aerated granules [69]. These values are qualified examples rather than a universal EUR/m³ premium and illustrate the sensitivity of economics to cultivation route, carrier,

nutrient system, protection method, and scale. To place bacterial self-healing in a broader technological context, Table 3 compares BSHCM with representative non-biological self-healing strategies. The reported performance values are study-specific and should not be interpreted as universal technology limits because crack geometry, exposure conditions, healing time, and evaluation methods differ among studies.

Table 3. Comparison of BSHCM with representative non-biological self-healing alternatives.

Approach	Mechanism	Representative Performance	Main Advantage	Implementation Issue	Ref.
Bacterial self-healing	Water activates viable/reactivable cells; metabolic mineralization	Performance varies strongly with strain, carrier, crack age, and exposure	Autonomous mineral formation; potential durability/service life benefit	Viability, nutrients, delayed cracking, attribution, cost, and by-products	[27,30]
Autogenous healing	Continued hydration, swelling, and abiotic carbonation	Generally, most effective for relatively narrow cracks; strongly binder- and moisture-dependent	No added healing agent or special processing	Limited crack width range; major confounder in bacterial studies	[4–6]
Superabsorbent polymers (SAPs)	Water uptake/swelling + promoted continued hydration	For 0.3 mm cracks, one study reported 85% lower peak flow and 98% lower total flow	Very rapid sealing; simple non-living admixture concept	Strength penalty; ionic-environment and dosage dependence	[70]
Crystalline admixtures	Moisture-driven crystal formation/continued reactions	Crack closure and permeability recovery are widely reported, but values depend strongly on crack width, matrix, and exposure	Commercially simple admixture route	Kinetics and functional recovery vary with matrix and exposure	[71]
Encapsulated mineral agents	Crack ruptures/dissolves capsule; mineral hydration/swelling	PEG/mineral capsules showed high sealing ratios below about 400 μm	No biological viability problem	Capsule survival, void/strength effects, mostly single-use release	[72]
Encapsulated polymer precursors	Crack ruptures capsule; liquid precursor flows and cures	Moving crack study: maximum stiffness regain about 35%; sealing can fail after further crack opening	Rapid sealing; useful for watertightness	Mechanical mismatch, capsule rupture, limited repeatability, embodied material burden	[73]

Note: Values are representative study-specific results, not universal technology limits. Direct numerical comparison is not valid unless crack geometry, exposure, healing time, and performance metrics are matched.

Overall, BSHCM offers a distinctive autonomous mineralization route, but its comparative advantage depends on whether biological viability and delayed healing translate into measurable functional durability gains under matched service conditions.

4. AI Readiness: Direct Evidence, Transferable Methods, and Validation Limits

Direct AI literature specific to BSHCM remains limited. To avoid presenting technological extrapolation as established practice, the evidence is separated here into three levels. Direct evidence includes studies that train or evaluate data-driven models using bacterial self-healing datasets or experiments. Transferable evidence includes methods from broader BSHCMs, crack image analysis, BSHCM informatics, or structural health monitoring that are technically relevant but have not yet been independently validated for BSHCMs. Prospective applications include closed-loop control, predictive maintenance, and digital twins that require standardized long-term datasets and validated links between measured signals and functional healing.

4.1. Directly Demonstrated Data-Driven Applications in BSHCM

Huang et al. assembled 797 literature-derived BSHCM cases with 22 input variables from 14 source articles and reported the best internal performance for gradient boosting regression ($R^2 = 0.956$; RMSE = 6.756%), with 10-fold cross-validation giving an average R^2 of 0.9438 [30]. These results demonstrate strong predictive performance within the assembled literature dataset, but independent external validation on a separately generated multi-laboratory or field dataset was not reported. The model is, therefore, best treated as a promising literature data proof of concept whose transferability depends on protocol harmonization and coverage of new bacterial, carrier, and exposure domains. Khosravi et al. compiled 1271 literature-derived cases and evaluated ANN-based hybrid models using a random 70/15/15 training/validation/testing split together with 10-fold cross-validation [29]. The ANN-LM model produced extremely high internal performance (test R^2 about 0.9997; average cross-validation R about 0.9960). These values require careful interpretation because residual crack width appears among the candidate inputs while healing percentage is the prediction target; since healing percentage is commonly calculated from initial and residual crack dimensions, feature provenance should be checked explicitly for potential target leakage. This is a validation concern, not evidence that leakage occurred. A further directly demonstrated BSHCM example is the ANN-supported optimization of an urban bacterial consortium for rapid crack healing reported by Šovljanski et al. [74], illustrating the use of AI as an experimental design and optimization tool within an explicitly bacterial healing system. Other direct or near-direct studies reinforce both the promise and the limits of the evidence. de Oliveira and Stefani reported random forest accuracy and F1 of 0.863 on a synthetic test dataset followed by verification on real cases, but the strong dependence on synthetic augmentation means that model behavior can inherit assumptions from the source data [75]. Tian et al. reported genetic-programming models with R^2 around 0.93 for crack repair prediction, while Meghashree et al. combined random forest and optimization with an experimental *Bacillus subtilis* system [41,76]. In the latter case, complete closure of cracks up to 1 mm within 21 days is a material outcome under the tested conditions and should not be presented as a model validation metric.

4.2. Experimental Optimization and Computational Comparators

Optimization can reduce the experimental burden in multi-variable BSHCM design, but statistical and AI methods should not be conflated. Response surface methodology (RSM) is a statistical design of experiments and response surface optimization method, not a form of AI. It is, therefore, treated here as a computational comparator. Intarasoontron et al. [77] used RSM to optimize bacterial spore encapsulation variables, while other studies have explored random forests, neural networks, genetic algorithms, particle swarm methods, and other search procedures [29,41,78]. The engineering objective should be

multi-criteria: crack sealing, transport recovery, viability, mechanical compatibility, cost, by-products, and environmental burden rather than crack closure alone.

4.3. Transferable Monitoring and Image Analysis Methods

Crack detection, segmentation, and time series monitoring methods are technically transferable to BSHCM, but most have been developed in broader structural health-monitoring contexts rather than validated specifically against bacterial healing. Accordingly, transferable methods should be labeled as such rather than described in the present tense as established BSHCM practice. Domain shift is likely when laboratory images, sensor ranges, crack morphologies, or curing conditions differ from field conditions. Prospective concepts such as predictive maintenance and digital twins may become useful only after the underlying measurement-to-performance relationships are validated on long-term BSHCM datasets [79–82]. Table 4, therefore, separates model performance from experimental material outcomes and reports validation design and external-validation limits explicitly.

CNN/FCN approaches can quantify crack geometry from images, while acoustic emission, electrical resistivity, humidity, temperature, and other sensors can provide time-resolved signals [83–85]. For BSHCM, these methods become scientifically meaningful only when imaging or sensor trends are linked to functional recovery and biological state; apparent surface closure should not be equated automatically with restored watertightness, transport resistance, or bacterial activity.

Table 4. Validation-aware evidence table for data-driven BSHCM and closely related self-healing studies.

Dataset/ Provenance	Model	Validation Design	Outputs and AI/Model Performance	External-Validation Limitation	Ref.
797 literature cases; 22 inputs; 14 source articles	SVR, DTR, DNN, GBR, RF	Train/test + grid search; 10-fold CV for GBR	GBR test $R^2 = 0.956$; RMSE = 6.756%; mean 10-fold $R^2 = 0.9438$	No separate multi-lab/field validation; study-level dependence and domain transfer remain concerns	[30]
1271 literature cases; 7 inputs + healing% target	ANN-GA, ANN-PSO, ANN-LM	Random 70/15/15 + 10-fold CV	ANN-LM test $R^2 \approx 0.9997$; mean CV $R \approx 0.9960$	Feature provenance should be checked for possible leakage; random split is not external validation	[29]
Limited real dataset expanded with synthetic data	NB, LR, KNN, SVC, RF	Synthetic train/test + verification on real cases	RF accuracy = 0.863; F1 = 0.863 on synthetic test set	Training relies strongly on synthetic augmentation; synthetic distribution can reproduce source data assumptions	[75]

Table 4. Cont.

Dataset/ Provenance	Model	Validation Design	Outputs and AI/Model Performance	External-Validation Limitation	Ref.
Study-derived data on bacterial/fiber BSHCM	GEP, MEP	Study-specific train/test assessment	$R^2 \approx 0.93$; reported RMSE ≈ 0.044 and MAE ≈ 0.033 for the best-performing model	No field external validation established; transfer to other bacterial/carrier domains uncertain	[76]
Experimental <i>Bacillus subtilis</i> BSHCM	RF + Kuhn- Tucker optimization	Study-specific	Model metric should be reported separately from material outcomes (100% closure of ≤ 1 mm cracks within 21 d under the tested conditions; reported increases of 9.3% in compressive strength, 12.8% in split tensile strength, and 6.36% in flexural strength)	Field validation not established; material outcome is not a model validation metric	[41]

4.4. Evidence Limits and Requirements for Trustworthy AI

High internal R^2 , accuracy, or F1 values should not be interpreted as evidence of broad engineering reliability unless the validation design supports that conclusion. Key questions include whether records from the same source study can appear in both training and testing sets; whether the target can be reconstructed from an input variable; whether hyperparameter selection used information from the final test set; whether synthetic data merely reproduce the assumptions of a small source dataset; and whether the model has been evaluated on independent laboratory, delayed cracking, or field data. For literature-aggregated BSHCM datasets, leave study out or study-grouped validation is more informative than a purely random split because it better approximates transfer to a new experimental campaign. Model uncertainty, class imbalance, measurement variability, negative results, and domain of applicability limits should also be reported. The present evidence, therefore, supports AI as a promising decision support tool, but not yet as a generally validated predictor across bacterial strains, carriers, mix designs, crack regimes, and service environments. Feature importance and explainability tools such as SHAP may help identify influential variables, but these associations should not be interpreted as causal evidence without mechanistic or experimental confirmation.

5. Research Priorities for AI-Ready BSHCM

The next research stage is not another layer of generic AI functionality but an evidence-to-deployment pathway that couples standardized BSHCM experiments with matched controls, machine-readable multimodal data, independent validation, and realistic exposure. Figure 5 summarizes this consolidated workflow. The sections below define the experimental and reporting requirements needed to move from proof of concept modeling toward trustworthy engineering support [86–88].

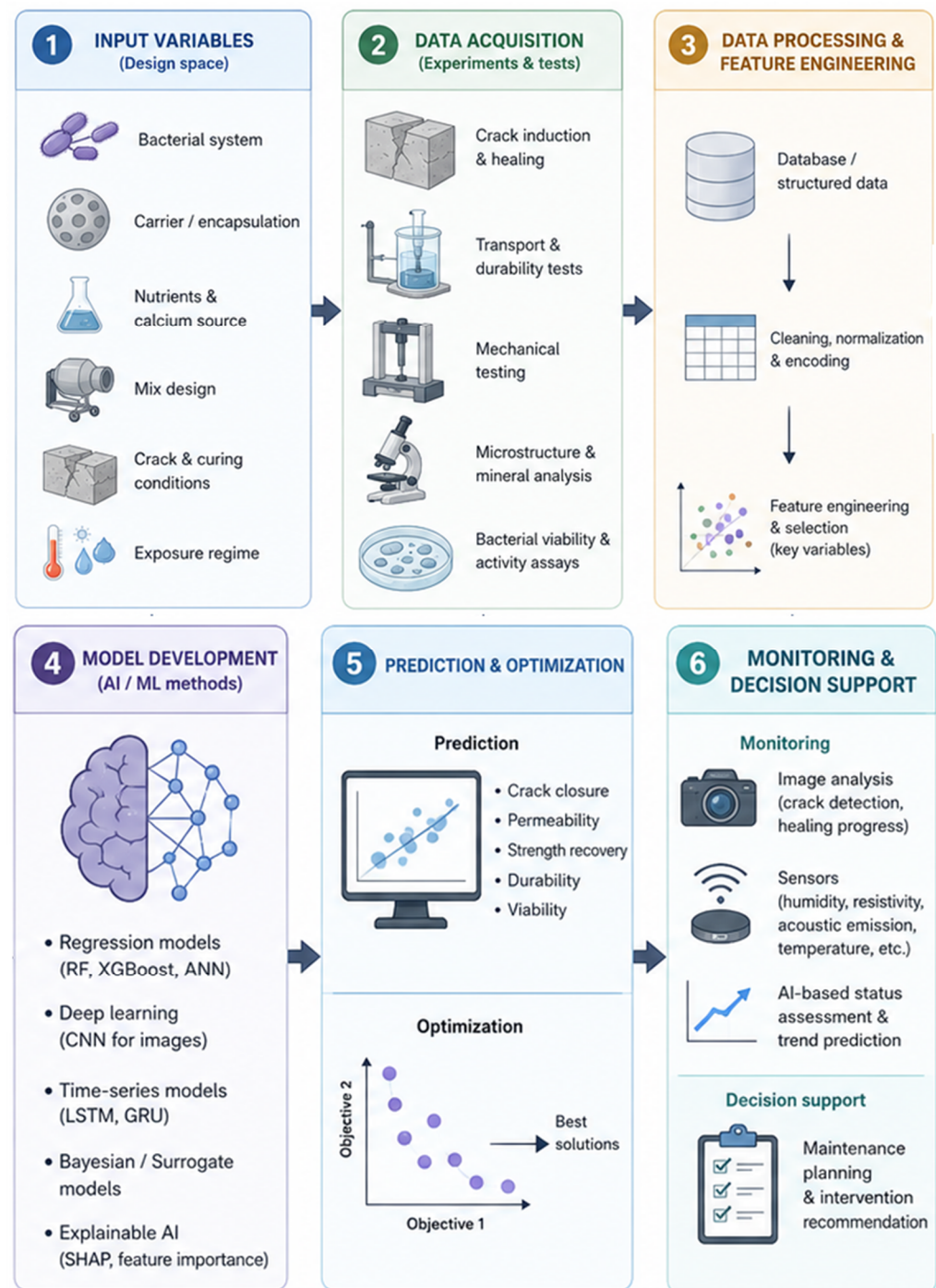


Figure 5. Consolidated AI-supported workflow for BSHCM, linking design variables and experimental data acquisition with data processing, model development, prediction/optimization, monitoring, and decision support. Independent validation on new laboratory, pilot, or field data should precede engineering deployment (BioRender was used for the preparation and graphical refinement of scientific illustrations).

Current heterogeneity in strains, carrier systems, crack generation procedures, crack width ranges, curing regimes, healing environments, and output metrics limits both reproducibility and ML transferability. Future studies should, therefore, be designed simultaneously as material experiments and reusable datasets: each input/output variable needs a defined unit, provenance, uncertainty, and relation to the physical mechanism. The three platform types summarized in Table 5 illustrate this progression.

Table 5. Experimental platforms for AI-ready BSHCM research.

Proposed Study	Aim	AI Models
Laboratory DOE	Identify Pareto-optimal combinations between healing, material properties, biological activity, and sustainability	Random forest/XGBoost for variable importance; Gaussian process + Bayesian optimization for the next experimental round
Sensorized specimens	Model healing kinetics in real time	CNN/FCN for crack segmentation; LSTM or Transformer for time series; multimodal fusion for “healed/healing/not healed” classification
Pilot prefabricated elements in aggressive environments	Verify scalability and maintenance under near-service conditions	Digital twin with probabilistic regression; remaining service life models; multi-criteria optimization of maintenance regimes

5.1. Standardized Reporting and Attribution Controls

Minimum reporting should cover bacterial species and strain, origin and identification, dormancy state, cell/spore concentration, viability before incorporation and after curing, pathway/activity indicators, carrier type and dosage, nutrient and calcium chemistry, mix design, crack induction method, crack age and width distribution, healing exposure, and output uncertainty. Functional outcomes should distinguish visual closure from permeability/sorptivity recovery, chloride or corrosion-related indicators, mechanical recovery where claimed, and mineralogical/microstructural evidence. Negative or failed results are essential because success-only datasets will bias future models toward overoptimistic predictions. Attribution of healing to bacterial activity requires an explicit minimum control set. At a minimum, studies should include (i) a reference mixture without the bacterial healing system; (ii) an otherwise identical carrier-only control without viable cells; (iii) an otherwise identical nutrient/calcium source control without viable cells; and (iv) the complete bacterial treatment [74]. Where technically justified, a sterilized or inactivated cell control can further separate biological from physicochemical effects. Crack width distributions, crack age, and exposure conditions must be matched across groups. XRD, Raman spectroscopy, SEM-EDS, and micro-CT can confirm the nature and location of precipitates, but mineralogy alone does not prove biological causation because abiotic and biogenic processes may form the same CaCO_3 polymorphs. Stable isotope or labeled substrate approaches can provide stronger pathway attribution where feasible. Without adequate abiotic controls, claims should be phrased as healing “associated with the bacterial system” rather than definitively “caused by bacterial activity.” These recommendations should build on existing pre-standardization activity rather than imply that the field starts from zero. Inter-laboratory programs under the EU COST Action SARCOS compared crack induction and healing assessment methods across six self-healing technology tracks. Published round robin work showed that crack width control, waterproofing details, specimen preparation, and test execution can materially influence measured sealing performance [86]. BSHCM-specific reporting and validation requirements should, therefore, extend these harmonization lessons while recognizing that no universally adopted normative standard for bacterial self-healing concrete has yet emerged.

5.2. AI-Ready Datasets and Data Structure

AI-ready datasets should organize each specimen or experimental condition as a traceable record with biological, carrier, nutrient, mix, crack, curing, and exposure inputs linked to functional healing outputs. Controlled terminology and standardized units are needed for bacterial pathway, carrier type, and exposure regime. Replicate number, standard deviation or confidence interval, missing data handling, and measurement uncertainty

should accompany mean values. Such metadata are necessary because BSHCM combines biological variability, heterogeneous cement-based matrices, and irregular cracks [87–89]. Image and sensor datasets require comparable metadata. Crack images should retain scale, resolution, illumination, acquisition method, crack age, and healing condition; processed masks should remain linked to raw images. Time series datasets should include timestamps, calibration, sampling rate, and environmental conditions. Without this information, apparent model accuracy may reflect laboratory-specific acquisition conditions rather than transferable crack or healing features [89–91].

5.3. Sensorized Laboratory Platforms

Sensorized platforms can complement endpoint testing by recording when environmental conditions permit activation and whether changes in transport or crack geometry persist. Humidity, temperature, electrical resistivity, acoustic emission, and imaging can be synchronized with periodic permeability, mineralogical, and viability measurements. The value of these signals is not their quantity but their causal linkage to functional healing; otherwise, multimodal models risk learning correlated but non-mechanistic proxies [83,87,91].

5.4. Sequential Experimental Design and Active Learning

Sequential design and Bayesian optimization may reduce the number of expensive BSHCM experiments by selecting informative next trials from a constrained design space [86–88]. This approach is attractive for delayed-cracking, long-term viability, chloride exposure, and pilot-scale studies, but proposed formulations should remain bounded by mechanistic constraints such as bacterial survival, nutrient solubility, carrier dosage, cement compatibility, and biosafety. Multi-objective optimization should balance sealing, transport recovery, viability, strength, cost, by-products, and environmental burden rather than maximize one output.

5.5. Pilot-Scale and Field Validation Platforms

Laboratory success does not establish field reliability. The experimentally observed dependence of bacterial self-healing performance on exposure conditions further supports the need for application-specific validation rather than extrapolation from a single laboratory curing regime [92]. Pilot and field programs should include delayed cracking after prolonged curing, realistic wet–dry or aggressive exposure, repeated loading where relevant, and monitoring long enough to test persistence of sealing and transport recovery. Application-specific endpoints may include watertightness, chloride resistance, corrosion delay, or freeze–thaw durability. These independently generated datasets are also the most important test of ML generalization because they expose models to new materials, crack histories, and environmental domains [83,84,88,93].

5.6. Digital Twins and Predictive Maintenance

Digital twins and predictive maintenance frameworks remain prospective for BSHCM. In principle, a dynamically updated model could combine mixture design, bacterial pathway, carrier system, crack history, environmental exposure, image data, and sensor signals to estimate the probability of functional healing or need for intervention. In practice, such a framework requires long-term datasets, reliable sensing, calibrated uncertainty, and validated relationships between monitored signals and durability outcomes. It should, therefore, be presented as a future deployment architecture rather than a mature current application [83,84].

5.7. Integration with Sustainability and Biosafety Assessment

Sustainability and biosafety should be integrated into experimental design rather than appended after performance testing. Lifecycle inventories should capture the added burden of cultivation, nutrients, carriers, and processing together with any verified reduction in repair, replacement, or structural material demand [27]. Biosafety reporting should include strain status and relevant by-products; ureolytic systems require attention to ammonium/ammonia, while nitrate-reducing pathways require appropriate nitrogen-species monitoring. Field deployment claims should, therefore, be supported by both functional performance and an application-specific environmental and biosafety assessment.

5.8. Limitations of the Review

This review has several scope-related limitations. First, the bibliometric and literature searches were restricted to Scopus in order to maintain a consistent and reproducible metadata structure for screening and VOSviewer analysis; consequently, relevant studies indexed exclusively in other databases may not have been captured. Second, the predefined publication window was limited to 2020–2025 because the review was designed to assess the contemporary development and AI readiness of bacterial self-healing cement-based materials rather than provide a historical reconstruction of the field. Third, the analysis focused on English language peer-reviewed publications, which may introduce language and publication bias and exclude potentially relevant non-English or gray literature. Accordingly, the conclusions should be interpreted within this defined evidence scope rather than as an exhaustive representation of all research conducted on bacterial self-healing cement-based materials.

6. Conclusions

Bacterial self-healing cement-based materials are technically credible but condition-dependent bio-mineral systems: successful crack sealing requires survival or reactivation of the biological component, access to water and substrates, matrix compatibility, and a crack geometry that permits transport and mineral growth. Surface closure alone is, therefore, insufficient evidence of durable healing, and bacterial causation cannot be inferred without appropriate abiotic controls. AI can add value primarily as a decision support layer for prediction, experimental design, image analysis, and multimodal monitoring. Current BSHCM-specific machine learning studies show promising internal performance, but the evidence base remains dominated by laboratory or literature-aggregated datasets with limited independent external and field validation. High R^2 , accuracy, or F1 values should, therefore, be reported together with data provenance, validation design, uncertainty, and domain of applicability limits. The most important near-term research priority is not a more complex algorithm but better evidence: harmonized experimental metadata, matched controls for autogenous and abiotic healing, delayed cracking and realistic exposure tests, machine-readable data including negative results and uncertainty, and comparative lifecycle/cost assessment against non-biological self-healing alternatives. Once such datasets exist across laboratories and pilot structures, AI can progress from promising proof of concept toward trustworthy engineering support.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/technologies14090575/s1>, Text S1: Literature Search and Keyword Co-occurrence Mapping; Table S1: Inclusion and exclusion criteria for SCOPUS analysis; Table S2: Co-Occurrence Analysis.

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L.P.; writing—original draft preparation, O.Š., A.K.S. and A.T.; writing—review and editing, L.P., A.K.S. and D.C.; visualization, L.P.; supervision, D.C. All authors have read and agreed to the published version of the manuscript.

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Glossary

BSHCM	Bacterial self-healing cement-based materials
MICP	Microbially induced carbonate precipitation
Autogenous healing	Healing arising from inherent cement-based reactions without an intentionally added healing agent
Autonomous healing	Healing produced by an intentionally engineered healing system
ML/DL	Machine learning/deep learning
ANN/RF/GBR	Artificial neural network/random forest/gradient boosting regression
RSM	Response surface methodology; a statistical design of experiments and optimization approach, not a synonym for AI

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