
EMERGING TECHNOLOGIES FOR SAFE ENGINEERING PRACTICES AND ENVIRONMENTAL PROTECTION: A SYSTEMATICALLY INFORMED, EVIDENCE-GRADED REVIEW WITH A PROPOSED NIGERIAN ADOPTION FRAMEWORK

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ABSTRACT

Emerging technologies are reshaping engineering safety and environmental protection, yet evidence on their cross-sectoral effectiveness and applicability in resource-constrained economies remains fragmented. This study synthesises peer-reviewed evidence on artificial intelligence (AI), the Internet of Things (IoT), digital twins and BIM, virtual reality and sensor fusion, drones, and nanomaterials across construction, mining, and oil and gas operations. A systematically informed narrative-review approach was adopted, combining a reported search and screening process with manual verification and an operationalised evidence-grading rubric. The discovery platform reported 8,652,714 cumulative topical matches across 23 searches and one citation-graph expansion, reflecting corpus scale rather than individually retrieved records; 250 records were then surfaced for human screening and progressively verified to identify the final 37-study evidence corpus. The synthesis indicates the strongest convergent evidence for IoT- and AI-enabled monitoring and hazard detection, while evidence for digital twins/BIM, immersive technologies, and nanotechnology-based remediation remains comparatively limited. Reported quantitative effects of 18–22% risk reduction and 58–70% safety improvement are treated as single-case findings rather than generalisable technology effects. The study further develops a twelve-dimension, indicative Nigerian technology-adoption framework covering cost, infrastructure, skills, maintenance, regulatory readiness, data governance, cybersecurity, organisational readiness, technology maturity, and safety and environmental benefits. The framework is presented as an analytical proposition requiring empirical validation rather than as evidence of current Nigerian conditions. Directly supporting ICESID 2026's theme of harnessing engineering for Nigeria's sustainable growth, the findings support phased adoption of scalable monitoring and predictive technologies alongside strengthened regulatory, cybersecurity, occupational-exposure, and workforce-development measures.

Keywords: emerging technologies; engineering safety; environmental protection; artificial intelligence; Internet of Things

1. INTRODUCTION

Engineering safety and environmental stewardship have historically been treated as compliance obligations layered onto production activity rather than as design objectives in their own right. This posture is changing. Artificial intelligence, the Internet of Things, digital twins, and automation are transforming safety management and environmental protection across construction, mining, and energy industries, reshaping how hazards are anticipated, monitored, and controlled (Adio et al., 2025; Dimkpa et al., 2025; Gobbo et al., 2018). The scale of the underlying problem is considerable: Gupta, Singh, Asari, and Nguyen (2026) report that construction, framed in their review as among the most hazardous industries globally, experiences a worker fatality approximately every ninety-nine minutes; their source does not further disaggregate this figure by country or region, and it is reported here exactly as framed in that review rather than with additional geographic precision the citing source does not itself provide. This statistic has nonetheless driven accelerating adoption of machine learning, robotics, wearable sensors, and immersive visualisation as complements to conventional safety management (Gupta et al., 2026). Parallel pressure is building on the environmental side of engineering practice, where Industry 4.0 concepts, the Internet of Things, big data, and cyber-physical systems, are increasingly framed as

opportunities to integrate process safety with environmental protection rather than treat them as competing priorities (Gobbo et al., 2018).

For Nigeria, these global dynamics intersect with structural realities that make emerging-technology adoption both more urgent and more difficult. The Nigerian economy remains heavily anchored on extractive and heavy-industry activity, oil and gas production in the Niger Delta, solid minerals mining, and an expanding construction sector, each carrying elevated occupational-safety and environmental-protection burdens. Environmental regulation is administered principally through the National Environmental Standards and Regulations Enforcement Agency (NESREA) and sector-specific upstream petroleum regulators, within an institutional environment that, as in many developing economies, faces resource and enforcement constraints. The oil and gas industry continues to contend with greenhouse gas emissions, spills, and process accidents that drive demand for more sustainable protection technologies across upstream, midstream, and downstream operations (Akerle et al., 2024; Alamutu, 2025; Okolie et al., 2024).

Despite this relevance, the literature on emerging technologies for engineering safety and environmental protection remains fragmented along sectoral and disciplinary lines, with comparatively little cross-sector synthesis and even less explicit engagement with the adoption conditions of developing economies. This paper addresses that gap and makes three specific contributions.

Knowledge contribution: a cross-sectoral, evidence-graded synthesis of six technology categories, AI and predictive analytics, IoT and real-time monitoring, digital twins/BIM, VR and sensor fusion, drones, and nanomaterials, against safety and environmental functions. Methodological contribution: an operationalised evidence-grading rubric applied transparently to a heterogeneous corpus, together with a reported search and screening protocol. Practice and policy contribution: a twelve-dimension technology-adoption framework that translates global evidence into a prioritisation logic for resource-constrained Nigerian engineering sectors, explicitly presented as a proposition for empirical validation. The objectives are to: (i) map the six technology categories against safety and environmental functions; (ii) characterise sector-specific applications and quantified impacts; (iii) grade the evidence using the stated rubric; and (iv) derive bounded implications for engineering practice, regulation, and workforce development in Nigeria.

2. LITERATURE REVIEW

2.1 Theoretical Foundations

The theoretical anchor for this review is the Industry 4.0 paradigm, which frames the convergence of cyber-physical systems, IoT, big data, and smart objects as a basis for simultaneously improving process safety and environmental performance rather than treating the two as a trade-off (Gobbo et al., 2018). Complementing this technological framing is a risk-governance perspective associated with the responsible-development literature, which holds that anticipation of hazards, precautionary approaches where occupational exposure limits are undefined, and transparent communication with exposed workers should accompany the introduction of any new technology into industrial practice (Schulte et al., 2024). A third theoretical strand, drawn from the Safe and Sustainable-by-Design (SSbD) literature, argues that environmental and health risk assessment should be embedded across a technology's full life cycle rather than appended after deployment (Cassee et al., 2024; Köhler & Som, 2014).

2.2 Classification Principle and Technology-Function Overlaps

The six technology categories used throughout this review, AI and predictive analytics, IoT and real-time monitoring, digital twins/BIM, VR and sensor fusion, drones, and nanomaterials, are organised by primary sensing, computation, or material function rather than by strict technical independence, because the underlying literature does not treat these as mutually exclusive systems. AI models frequently operate on data streams generated by IoT sensor networks; digital twins depend on both IoT inputs and analytics engines to remain synchronised with the physical asset they represent; drones increasingly embed AI-based computer vision for autonomous inspection; and VR/sensor-fusion training platforms can draw on the same spatial data underlying a digital twin. Nanomaterials are the clear exception, differing fundamentally from the other five categories as a materials-science rather than

a digital/computational technology. Table 1 presents a technology-function matrix that makes this overlap explicit, classifying each category by its dominant function rather than treating the six categories as structurally independent silos.

Table 1: Technology-Function Matrix, Showing Dominant and Secondary Functions

Technology	Dominant Function	Secondary/Overlapping Function	Principal Sectors
AI & predictive analytics	Computation / prediction	Embedded within IoT and drone systems	Mining, construction, oil & gas
IoT & real-time monitoring	Sensing	Supplies data to AI, digital twins	Industrial, mining
Digital twins & BIM	Visualisation / simulation	Depends on IoT + analytics inputs	Construction, oil & gas
VR & sensor fusion	Visualisation / training	Overlaps with digital-twin spatial data	Mining, occupational safety
Drones	Sensing (remote/aerial)	Increasingly AI-embedded (computer vision)	Industrial, environmental
Nanomaterials	Materials intervention	None (non-digital category)	Environmental remediation, oil & gas

2.3 AI and Predictive Analytics

AI-enabled predictive analytics is among the most consistently reported technology categories in the corpus, applied to hazard detection, predictive maintenance, and environmental-risk forecasting across construction, mining, and oil and gas operations (Adio et al., 2025; Dimkpa et al., 2025; Arjunan et al., 2025). In oil and gas operations, machine-learning-based predictive analytics forecasts potential equipment failures and schedules proactive maintenance, complementing continuous IoT-based condition monitoring (Akpe et al., 2024). Systematic reviews of construction-safety technologies identify AI-based topic modelling and smart-technology integration as tools that proactively identify hazards, reduce accidents, and improve resource allocation, while simultaneously contributing to lower carbon emissions through better energy optimisation on site (Seo & Yoon, 2025).

2.4 IoT and Real-Time Monitoring

IoT-based sensing underpins much of the reported progress in both safety and environmental monitoring. In underground mining, an IEEE review documents IoT architectures purpose-built for simultaneous environmental, safety, and production monitoring, addressing persistent challenges such as limited battery life and unreliable underground communication (Zhang et al., 2023). Low-cost sensor networks are identified as a foundational enabling layer for Industry 4.0 digital transformation in mining, supporting real-time monitoring through wireless networks in combination with AI, machine learning, and digital twins (Cacciuttolo et al., 2023). More broadly across industrial operations, digital HSE technologies, encompassing IoT-enabled compliance monitoring alongside AI-based analytics, are reported to strengthen health, safety, and environmental management practice (Adikwu et al., 2024). A single regional mining-complex case study reports that integrating information technologies with environmental monitoring data was associated with an 18–22% reduction in overall industrial and environmental risk at that site; this figure derives from a before–after design at one location without independent replication, and should be read as a case-specific reported effect rather than an expected or generalisable improvement (Kukartsev et al., 2025).

2.5 Digital Twins, BIM, and Robotics

Digital twin technology, providing virtual replicas of physical assets, is reported to enable risk-free simulation and optimisation of plant operations in oil and gas contexts (Akpe et al., 2024). In construction, BIM, robotics, wearable devices, and AI are each positively and significantly associated with improved safety performance, with BIM and wearable technologies showing the strongest individual effects in comparative analysis (Dobrucalı et al., 2022; Yap et al., 2021). The principal safety-enabling mechanisms identified are improved hazard identification, reinforced safety planning, and enhanced monitoring and supervision (Yap et al., 2021). A systematic review of 129 journal articles published between 2018 and 2023 organises construction safety technologies across four functional areas, prevention through design, safety management, safety culture and awareness, and computing in construction safety (Maali et al., 2024). BIM, drones, and prefabrication techniques together enable real-time monitoring, hazard detection, and improved stakeholder coordination, with reported reductions in accident likelihood in high-rise construction (Kumar et al., 2025).

2.6 VR, Drones, and Immersive Technologies

VR and sensor-fusion technologies are applied principally to hazard-scenario training and ergonomic assessment, with secondary applications in pollution visualisation and ecological education (Strzałkowski et al., 2025). Review evidence spanning geodesy and geomatics, mining, environmental protection, and occupational safety identifies sensor-integrated immersive training as a growing sub-field with demonstrated training value, though empirical evidence on transfer to real-world safety outcomes remains comparatively thin (Strzałkowski et al., 2025). Drones are reported primarily as tools for remote inspection and large-scale environmental monitoring, extending the geographic reach of safety and compliance surveillance without placing personnel in hazardous locations (Dimkpa et al., 2025).

2.7 Nanotechnology, Advanced Materials, and Environmental Remediation

Environmental engineering is increasingly linked to Industry 4.0 through intelligent monitoring, low-carbon processes, and data-driven environmental management. Emerging technologies can support emissions, water, pollution, and ecological monitoring, but the environmental evidence is less mature than the safety evidence. Sensor networks and AI offer scalable monitoring and prediction, while nanomaterials provide remediation pathways but introduce exposure and life-cycle concerns (Ateia et al., 2024; Liu et al., 2024; Wu et al., 2024).

These exposure and life-cycle concerns are well documented at the level of individual nanomaterial applications. Advanced *in vitro* and *in silico* safety-assessment tools are increasingly used to characterise the hazard profile of engineered nanomaterials ahead of deployment, reducing reliance on animal testing while improving mechanism-based risk characterisation (Fadeel et al., 2018). Life-cycle-oriented reviews of the nano-world more broadly identify environmental risk as distributed across a material's full production-to-disposal pathway rather than concentrated at the point of use, reinforcing the case for safe-and-sustainable-by-design approaches introduced in Section 2.1 (Glišović et al., 2017). Sector-specific evidence extends this concern to oil and gas operations directly relevant to the Nigerian context examined in this review: nanoparticle additives used in drilling muds improve technical performance but carry environmental, health, and safety implications that remain incompletely characterised, underscoring the need for occupational-exposure guidance to accompany, rather than follow, adoption (Martin et al., 2023).

2.8 Distinguishing Safety and Environmental Protection Outcomes

The review therefore distinguishes environmental monitoring from broader environmental protection. Monitoring applications have comparatively direct evidence, whereas pollution prevention, remediation, and governance remain more dependent on laboratory studies, reviews, and conceptual work. Forward-looking technology-forecasting reviews frame environmental engineering itself as entering a period of disruptive innovation, driven by sensing, data, and materials advances converging on pollution-prevention applications (Huang, Lu, Jin, & Ren, 2024), while membrane-based separation technologies illustrate the more laboratory-proximate evidence base typical of remediation applications specifically, with emerging directions targeting pollutant removal and degradation in aqueous systems

(Zhao et al., 2024). This distinction is retained in the evidence grading and in the Nigerian adoption framework.

Table 2: Depth of Empirical Coverage Across Safety and Environmental Outcome Categories

Outcome Category	Representative Evidence	Predominant Evidence Type
Occupational safety	Akinlolu et al. (2020); Yap et al. (2021); Dobrucalı et al. (2022)	Systematic reviews; site-level observational studies
Process / industrial safety	Di Martino et al. (2021); Benson et al. (2023); Akpe et al. (2024)	Case studies; conceptual frameworks
Environmental monitoring	Zhang et al. (2023); Cacciuttolo et al. (2023); Kukartsev et al. (2025)	Technical reviews; single-site case study
Pollution prevention	Huang et al. (2024); Ateia et al. (2024)	Conceptual / technology-forecasting reviews
Environmental remediation	Liu et al. (2024); Wu et al. (2024); Zhao et al. (2024)	Laboratory-scale evidence; narrative reviews
Environmental risk governance	Schulte et al. (2024); Cassee et al. (2024); Köhler & Som (2014)	Policy/framework papers

Table 2a complements this outcome-based view with a technology-based one, tracing each of the six technology categories through to its specific environmental application, the evidence maturity behind that application (using the same strong/moderate/weak logic operationalised in Table 4), and its plausible relevance to the Nigerian sectors discussed in Section 4.4. This technology-to-environmental-function view is intended to strengthen the environmental half of the review's dual safety/environmental scope without duplicating the outcome-category analysis in Table 2.

Table 2a. Technology-to-Environmental-Function Synthesis, with Evidence Maturity and Indicative Nigerian Relevance

Technology	Environmental Application	Evidence Maturity	Indicative Nigerian Relevance
IoT	Emissions, water, and ambient environmental monitoring	Strong–moderate	High — low-cost, scalable entry point (Section 5)
AI	Environmental-risk prediction and forecasting	Moderate	High — pairs naturally with IoT data streams
Drones	Remote environmental surveillance over large or hazardous areas	Moderate	High — extends monitoring reach without fixed infrastructure
Digital twins / BIM	Process optimisation and emissions reduction	Moderate	Moderate — constrained by capital cost and infrastructure (Table 8)
Nanomaterials	Soil, water, and pollutant remediation	Moderate	Potentially high, but safety-constrained pending exposure-limit clarity
VR / sensor fusion	Environmental and safety training, pollution visualisation	Limited	Moderate — training value plausible; outcome evidence thin

2.9 Critical Synthesis and Identified Gap

Across the six technology categories, the literature reports measurable safety and environmental benefits, but the evidence is dominated by reviews, conceptual frameworks, and single-site case studies rather than large empirical trials. Emerging technologies can also introduce new failure modes, occupational exposures, cybersecurity risks, and governance gaps (Salmon et al., 2024; Schulte et al., 2024). Technological-forecasting perspectives on environmental innovation caution more broadly that emerging technologies diffuse unevenly across institutional and economic contexts, so that global evidence of technical feasibility does not, by itself, predict the pace or pattern of adoption in any specific setting (Kargı & Coccia, 2024), a caution directly relevant to the Nigerian adoption framework developed in Section 4.4. Adoption barriers include cost, infrastructure, skills, organisational resistance, and regulatory capacity, with limited evidence from developing economies. The central gap is therefore not the absence of technological capability, but the limited empirical basis for determining how emerging technologies should be prioritised and governed in Nigerian engineering contexts.

3. MATERIALS AND METHODS

3.1 Review Design and Terminology

The review is designated a systematically informed narrative review rather than an unqualified systematic review. The latter typically requires dual independent screening, inter-rater reliability, and formal quality appraisal, which were not fully available here. The present design instead combines a reported search and screening process, manual verification, and an explicit evidence-grading rubric suited to a heterogeneous cross-sector corpus.

This hybrid label requires clarification given that Section 3.3 presents a four-stage, structured study-selection flow table styled after common systematic-review reporting conventions, and Section 3.5 presents a structured evidence-grading rubric, both of which are apparatus more commonly associated with systematic reviews. Three systematic-review elements were adopted: a staged, numerically reported selection process (Table 3); an explicit, reproducible grading rubric applied uniformly across included studies (Table 4); and transparent reporting of exclusion counts between stages. Three systematic-review elements were not adopted, and are flagged as limitations in Section 3.6: dual independent screening with an inter-rater reliability statistic; a pre-registered protocol; and a formal, validated quality-appraisal instrument (e.g., MMAT or CASP) in place of the purpose-built rubric. The review therefore sits deliberately between the two traditions, borrowing the transparency mechanisms of a systematic review while not claiming the full methodological guarantees, particularly independent replicability of the screening decisions, that the unqualified term would imply.

3.2 Search Strategy and Sources

The literature search used Consensus, an AI-assisted academic discovery platform, as a search-support tool. Four term groups were developed around emerging technologies, safety/environmental outcomes, engineering sectors, and developing-economy context. Twenty-three searches and one citation-graph expansion together produced an initial platform-reported count of 8,652,714 cumulative topical matches; the citation-graph expansion is included within, not additional to, this count. This figure warrants explicit clarification: it is the cumulative count of instances the platform's interface reported as topically matching one of the 23 queries or the citation-graph expansion against its full indexed corpus, which spans over 170 million papers, before deduplication, relevance ranking, or any manual review. It should be read as an indicator of the breadth of the underlying indexed corpus and the deliberately broad initial term groups used, not as a set of records that were individually retrieved, inspected, or screened; no claim is made that this number represents discrete, non-overlapping documents, and the figure is not itself labelled or treated as "records retrieved" anywhere else in this paper. The operationally meaningful figure, and the one from which all subsequent screening in Table 3 proceeds, is the 250-record set the platform's relevance-ranking algorithm surfaced for detailed human screening. The platform was used only to identify this manageable screening set; all inclusion decisions from that point forward were checked manually. Because the platform is proprietary, its ranking model and complete search logs are not independently auditable.

3.3 Study Selection Process

Table 3 summarises the four-stage selection process from identification to inclusion, presented as a study-selection flow table rather than a graphical flow diagram.

Table 3: Study Selection Flow, from Initial Identification to Final Inclusion

Stage	N	Process Applied
1. Identification	8,652,714	Cumulative platform-reported topical matches across 23 searches (4 term groups) + 1 citation-graph expansion, against the platform's indexed corpus (>170M papers); not individually retrieved or screened records
2. Screening	250	Platform relevance-ranking algorithm surfaced top-ranked records for detailed screening; deduplication applied
3. Eligibility	198	Records meeting topical relevance and minimum quality signal (peer-reviewed venue; explicit safety/environmental engineering application) after deduplication
4. Inclusion	37	Final selection of records with complete, independently verifiable bibliographic data, applying the explicit rule set out below

Inclusion criteria required that a paper (i) be published in a peer-reviewed journal or conference proceedings, (ii) report on at least one emerging technology applied to engineering safety, environmental protection, or both, and (iii) situate that application within an identifiable industrial sector. Papers addressing emerging technologies purely from a non-engineering perspective were excluded at Stage 3. Reasons for exclusion between Stage 2 and Stage 3 (52 records) were topical irrelevance on full-abstract reading and absence of an identifiable engineering-sector application; a record-level exclusion log was not retained in exportable form and is noted as a reproducibility limitation in Section 3.6. Journal articles and conference proceedings were both eligible and were not differentiated by a separate quality-weighting scheme; this is likewise flagged as a limitation, since venue type can correlate with review rigour.

The Stage 3-to-Stage 4 transition requires clarification, since eligibility (198 records) and final inclusion (37 records) differ substantially and this attrition should not be read as arbitrary. “Complete, independently verifiable bibliographic data” means, concretely, that a record carried a full author list, publication year, journal or proceedings title, volume/issue and page range (or article number), and a resolvable DOI or equivalent stable identifier (e.g., a persistent publisher URL) that could be checked against an independent source rather than taken on the platform's metadata alone. Records were dropped between eligibility and inclusion primarily for three reasons: incomplete platform-exported metadata, most commonly a missing or malformed DOI, common among conference proceedings and recently published articles not yet fully indexed; inability to independently verify the record against a second source, since platform-only metadata was not treated as sufficient on its own after the verification issues discussed in Section 3.4; and, in a smaller number of cases, records that on closer full-text reading did not, in fact, report a specific, attributable technology application meeting the inclusion criteria despite passing automated relevance screening. The 81 percent attrition between eligibility and inclusion is therefore substantially a function of the verification standard applied, deliberately stringent, given the citation-integrity concerns that motivated Section 3.4, rather than of topical irrelevance, which had already been filtered out at the earlier eligibility stage. The platform synthesis referenced a target pool of up to 50 topically relevant records within the eligible set; of these, 37 satisfied the full bibliographic-verification standard above. The final evidence corpus is therefore defined as the 37 fully verified studies. No additional records were inferred, fabricated, or counted without verifiable bibliographic support. Tables and conclusions use 37 as the denominator unless explicitly stated otherwise.

3.4 Role of AI-Assisted Discovery and Human Verification

The Consensus relevance-ranking algorithm narrowed the very large initial pool to a manageable screening set and ranked the eligible records for further consideration. It is treated only as

a search-support mechanism, not as an independent methodological authority. The model is proprietary and its ranking weights are not independently auditable; consequently, manual verification was used for final inclusion. Exact platform query strings, execution dates, and ranking scores were not retained, which limits exact replication.

3.5 Data Extraction and Evidence-Grading Rubric

Data extracted from each retained paper included technology category, sector, reported safety or environmental function, any quantified outcome measures, and stated limitations or barriers. Table 4 sets out the explicit rubric applied. Each claim synthesised in Section 4.3 was scored against five criteria, number of independent supporting studies, predominant study-design quality, presence of replication, geographic diversity of the supporting evidence, and the nature of outcome measurement.

Table 4: Operationalised Evidence-Grading Rubric

Criterion	Low / Weak Signal	Moderate Signal	High / Strong Signal
Number of independent studies	1 study	2–3 studies	4+ independent studies
Study design quality	Conceptual / opinion	Observational / single case study	Multiple observational or quasi-experimental studies
Replication	None	Limited (1 corroborating source)	Multiple independent corroborations
Geographic / contextual diversity	Single site or region	2–3 regions or sectors	4+ regions or sectors
Outcome measurement	Qualitative / descriptive only	Proxy or partial quantitative measure	Direct, quantified outcome measure

The overall strong/moderate/weak grade was not derived from a mechanical count of how many of the five criteria fell into each band. Instead, the default rule was that a grade required at least three of the five criteria to point in the same direction, with the more conservative (lower) grade assigned wherever the criteria diverged. This default was overridden in one specific, explicitly flagged circumstance: where a claim rested on a single case but that case reported a direct, quantified outcome measure (the strongest of the five criteria) rather than a qualitative or proxy measure, the claim was graded moderate rather than weak, on the reasoning that a precisely measured single-case effect carries more evidentiary weight than an equivalently single-source qualitative judgement, while still falling well short of a claim replicated across independent, geographically diverse studies. This override applies to exactly two claims in Table 7, both flagged there with an asterisk and explained in the accompanying note; every other grade in Table 7 follows the default majority rule without exception. This exception-based logic, rather than a strict unweighted vote across the five criteria, is what Table 7 reports, and it is disclosed here explicitly so the grading is reproducible rather than merely asserted.

This rubric was applied retrospectively to the corpus rather than pre-registered, which is itself a limitation relative to full systematic-review practice; it nonetheless represents a substantial improvement in transparency and reproducibility over an unstructured strong/moderate/weak judgement, and the platform's own algorithmically generated evidence-reasoning summaries were cross-checked against, rather than substituted for, this manual rubric.

3.6 Methodological Limitations

The following limitations qualify, but do not negate, the value of the synthesis; they define the boundary of what the review can credibly claim, which is an evidence-graded narrative synthesis that is transparent and reproducible in its reported screening logic and grading rubric, but not fully reproducible at the level of the underlying platform searches themselves, given the search-log limitation noted below, rather than a protocol-registered systematic review with meta-analytic pooling.

- 50-versus-37 record discrepancy: the discovery platform referenced up to 50 relevant records, but only 37 carried complete, independently verifiable bibliographic detail on export; the manuscript therefore uses the 37 verified studies as its evidence corpus.
- Single-analyst screening: no second independent reviewer and no inter-rater reliability statistic is available.
- Proprietary relevance algorithm: the Consensus ranking model is not independently auditable, and false negatives (relevant papers never surfaced) could not be assessed.
- Search-log limitation: exact platform query strings, execution dates, and platform-generated ranking scores for the 23 individual searches were not retained, limiting exact replication of the search process; Section 3.2 reports an illustrative representative formulation in place of a verbatim log.
- No formal quality-appraisal instrument (e.g., MMAT, CASP) was applied; the evidence-grading rubric in Table 4 is a purpose-built substitute, not an equivalent.
- No language restriction was explicitly enforced, and the retained corpus is entirely English-language by outcome rather than by declared protocol.
- Journal articles and conference proceedings were not differentiated by a separate quality weighting.
- A record-level exclusion log for the 52 records dropped between screening and eligibility was not preserved in exportable form.
- Drones, while discussed qualitatively as one of the six technology categories throughout Section 2, were not separately coded in the quantitative outcome-frequency matrix (Table 9) during data extraction, and are therefore absent from that table; no drone-specific frequency counts have been estimated or invented to fill this gap.

4. RESULTS

Table 5 summarises illustrative studies from the retained corpus, selected to represent the range of technology categories, sectors, and evidence types synthesised in Section 2. This table reports only the study-level detail available from the extracted source material; it is presented as a representative subset of the 37 verified included studies rather than an exhaustive table of all 37, since location, sample size, and full methodological detail were not uniformly retrievable for every included paper, itself a data-extraction limitation noted in Section 3.6.

EMERGING TECHNOLOGIES FOR SAFE ENGINEERING PRACTICES AND ENVIRONMENTAL PROTECTION: A SYSTEMATICALLY INFORMED, EVIDENCE-GRADED REVIEW WITH A PROPOSED NIGERIAN ADOPTION FRAMEWORK

Table 5: Representative Studies from the Reviewed Corpus, by Technology Category and Sector

Study	Technology Focus	Sector / Context	Principal Finding	Evidence Type
Akinlolu et al. (2020)	Construction safety technologies (bibliometric)	Construction	Maps research architecture of 240 construction-safety technology papers	Bibliometric review
Zhang et al. (2023)	IoT architectures	Underground mining	IoT enables simultaneous environmental, safety, and production monitoring	Technical review
Kukartsev et al. (2025)	Integrated IT / environmental monitoring	Regional mining complex	18–22% reduction in industrial/environmental risk (single site)	Case study
Di Martino et al. (2021)	Inherently safer design (ISD) framework	Chemical / process industry	58–70% safety improvement (single case)	Case study
Maali et al. (2024)	Construction safety technologies (taxonomy)	Construction	Categorises 129 articles (2018–2023) into four safety-technology functions	Systematic review
Yap et al. (2021)	BIM, robotics, wearables	Construction (Malaysia)	BIM and wearables show strongest individual safety effects	Empirical / survey study
Cacciuttolo et al. (2023)	Low-cost IoT sensors	Mining	Sensor networks as foundational layer for Industry 4.0 mining transformation	Systematic review
Liu et al. (2024)	Nanoparticle remediation	Soil and water	Nanoparticles function as efficient sorbents/catalysts for pollutant removal	Narrative review
Wu et al. (2024)	Functional nanomaterials	Environmental remediation	Calls for Safe and Sustainable-by-Design given unresolved exposure limits	Narrative review
Kuppula & Bhawani (2025)	Exoskeletons, jobsite technology	Construction	Productivity gains alongside unresolved long-term worker-health concerns	Thematic analysis

4.1 Sector Comparison: Mining and Oil and Gas

Both sectors rely on IoT sensing and automation as a core safety mechanism, but the specific hazard managed, and the quantified impact reported, differ, as summarised in Table 6. In mining, automation and remote-controlled equipment reduce human exposure to hazardous conditions and improve emergency response (Onifade et al., 2023; Arjunan et al., 2025); in oil and gas, offshore drilling safety advances include spill-prediction models, automated safety protocols, and emission-control measures such as carbon capture and flare-gas recovery (Alamutu, 2025). As already noted in Section

2.4, the 18–22% and 58–70% figures reported below are single-case findings and are not to be read as expected sector-wide effects.

Table 6: Comparison of Mining and Oil and Gas Safety Technology Applications

Dimension	Mining	Oil and Gas
Core technology	IoT sensors, automation, remote equipment	Real-time monitoring, predictive analytics, digital twins
Safety mechanism	Reduces human exposure to hazardous conditions	Detects anomalies before escalation
Environmental function	Proactive geotechnical and gas monitoring	Spill prediction, emissions control
Key barrier	Battery life; underground communication quality	Integration with legacy systems
Reported impact (single case; not generalisable)	18–22% risk reduction with integrated IT	58–70% safety improvement with ISD framework

4.2 Construction-Sector Evidence

Construction-sector evidence is comparatively richer in systematic reviews. A bibliometric analysis of 240 construction-safety technology papers establishes the field's overall research architecture (Akinlolu et al., 2020), while a subsequent systematic review of 129 articles (2018–2023) categorises construction safety technologies across four functional areas (Maali et al., 2024). Smart technologies, digital twins, IoT, and big data, are reported to enhance construction-site safety proactively while simultaneously optimising energy use and lowering carbon emissions (Seo & Yoon, 2025). This benefit is not unqualified: emerging construction technologies also introduce sustainability challenges of their own, including high energy consumption, electronic-waste generation, elevated implementation costs, and labour-market disruption, with exoskeletons specifically flagged as improving short-term productivity while raising unresolved questions about long-term musculoskeletal health, a claim graded weak in Table 7 given its reliance on a single thematic-analysis finding (Kuppula & Bhawani, 2025).

4.3 Evidence-Strength Assessment

Applying the operationalised rubric in Table 4 and the exception rule described in Section 3.5, Table 7 grades the strength of evidence behind the review's principal claims and reports the rubric criteria underlying each grade, rather than an unexplained qualitative label. The strongest-graded claim, that IoT and AI improve safety monitoring and hazard detection, is supported by four or more independent, high-quality sources converging across mining, construction, and oil and gas, with quantified outcome measures reported in at least two of those sources (Zhang et al., 2023; Dimkpa et al., 2025; Seo & Yoon, 2025; Akpe et al., 2024). Claims regarding digital twins/BIM and nanotechnology remediation are graded moderate under the default majority rule, reflecting two to three supporting studies with predominantly observational or conceptual designs and limited geographic diversity. The two single-case quantitative claims (18–22% and 58–70%) are graded moderate under the explicit exception described in Section 3.5, since a direct, quantified single-case outcome measure was judged to carry more evidentiary weight than an equivalent single-source qualitative claim, while still falling short of the replication and geographic-diversity needed for a strong grade. The weakest-graded claim, concerning exoskeleton health effects, satisfies none of the five criteria beyond a single qualitative source and receives the default weak grade with no exception applied.

EMERGING TECHNOLOGIES FOR SAFE ENGINEERING PRACTICES AND ENVIRONMENTAL
PROTECTION: A SYSTEMATICALLY INFORMED, EVIDENCE-GRADED REVIEW WITH A
PROPOSED NIGERIAN ADOPTION FRAMEWORK

Table 7: Evidence Strength for Key Claims, Graded Against the Rubric in Table 4

Claim	Independent Studies	Design Quality	Replication	Geographic Diversity	Overall Grade
IoT and AI improve safety monitoring and hazard detection	4+	Observational/quasi-experimental (multiple)	Multiple	4+ sectors	Strong
Digital twins/BIM enhance construction safety via proactive hazard identification	2–3	Observational + conceptual	Limited	2–3 contexts	Moderate
Nanotechnology enables remediation but poses toxicity risks requiring SSbD	3+	Laboratory / conceptual	Limited	Single domain (materials)	Moderate
Integrated IT deployment reduces industrial/environmental risk by 18–22%	1	Single case study	None	Single site	Moderate*
ISD framework improves safety by 58–70%	1	Single case study	None	Single site	Moderate*
Exoskeletons raise long-term worker-health concerns	1	Thematic analysis (qualitative)	None	Single context	Weak

*Graded moderate under the explicit exception in Section 3.5: a direct, quantified single-case outcome measure outweighs the single-study and no-replication criteria that would otherwise default to weak, but does not itself constitute evidence of generalisability — see Section 4.1 and the case-specific labelling applied throughout.

4.4 A Conceptual/Indicative Nigeria-Specific Adoption Framework

None of the 37 studies in the final synthesis reported an empirical Nigerian or West African case. The framework in Table 8 is therefore presented as a conceptual/indicative adoption framework, not an adoption index or measured assessment of Nigerian conditions. Its ratings are author judgments derived from the reviewed evidence and contextual reasoning, not Nigerian survey data, Delphi ratings, frequency counts, or weighted scores. The framework is a structured starting point for empirical validation and scores four priority technology groupings against twelve adoption-relevant dimensions using Low/Moderate/High ratings.

Table 8: Conceptual/Indicative Nigeria-Specific Technology-Adoption Framework (Author Judgment, Not a Measured National Readiness Index; Requires Empirical Validation)

Dimension	IoT / AI Monitoring	Digital Twins / BIM	VR Safety Training	Nanotech Remediation
Capital cost	Low–Moderate	High	Moderate	Moderate–High
Technical infrastructure need	Low–Moderate	High	Moderate	Moderate
Electricity/connectivity reliability need	Moderate	High	Moderate	Low
Skills availability (current)	Moderate	Low	Low	Low
Maintenance capacity required	Moderate	High	Moderate	Moderate
Regulatory readiness	Low	Low	Low	Low
Data governance exposure	Moderate	Moderate	Low	Low
Cybersecurity exposure	Moderate–High	Moderate	Low	Low
Organisational readiness	Moderate	Low	Low–Moderate	Low
Technology maturity (global)	High	Moderate–High	Moderate	Moderate
Environmental benefit (global evidence)	Moderate	Low–Moderate	Low	High
Safety benefit (global evidence)	High	Moderate	Moderate	Low

Read across dimensions, the framework indicates that IoT/AI monitoring combines the most favourable near-term adoption profile (comparatively low capital and infrastructure requirements against the strongest global safety-evidence base) with a genuine governance gap (low regulatory readiness, moderate-to-high cybersecurity exposure) that Nigerian regulators would need to address concurrently with, not after, deployment. Digital twins/BIM and nanotechnology remediation both show a wider gap between global technology maturity/environmental promise and local readiness (skills, infrastructure, or regulation), consistent with the near-total absence of developing-economy evidence identified in Section 4.5.

4.5 Research Gaps by Outcome Dimension

The 37-study corpus provides an uneven picture of evidence coverage. Counting, within the verified papers, how many address each of five outcome dimensions per technology category, Table 9 shows comparatively stronger empirical coverage for IoT safety monitoring and nanotechnology remediation, moderate coverage for AI predictive analytics and VR safety training, and less coverage for digital twins. Developing-economy evidence is particularly sparse: AI, VR, and digital twins record no papers specifically addressing such contexts, while IoT and nanotechnology each have only one. Drones are not separately coded in this matrix and are therefore excluded from the frequency counts.

EMERGING TECHNOLOGIES FOR SAFE ENGINEERING PRACTICES AND ENVIRONMENTAL
PROTECTION: A SYSTEMATICALLY INFORMED, EVIDENCE-GRADED REVIEW WITH A
PROPOSED NIGERIAN ADOPTION FRAMEWORK

Table 9: Number of Included Papers (of 37) Addressing Each Outcome Dimension, by Technology Category
(Drones Not Separately Coded)

Technology	Empirical Validation	Long- Term Safety	Cost- Effectiveness	Developing Economies	Regulatory Frameworks
IoT safety monitoring	8	3	2	1	4
AI predictive analytics	6	2	1	0 (gap)	3
Nanotechnology remediation	9	5	2	1	4
VR safety training	5	1	2	0 (gap)	2
Digital twins	4	1	1	0 (gap)	2

This exclusion has a direct implication for how the gap analysis in this section should be read: because drones are not separately coded in Table 9, the research-gap picture presented here characterises five of the review's six technology categories rather than all six, and the apparent evidence coverage of the reviewed corpus as a whole is correspondingly incomplete rather than exhaustive. Drone-specific applications are still discussed qualitatively in Section 2.6 and appear in the technology-function matrix (Table 1) and the environmental-function synthesis (Table 2a), so the omission is confined to this specific outcome-dimension frequency count rather than to the review's coverage of drones generally; a coded drone row is identified in Section 3.6 as a specific target for the data-extraction protocol in any future update of this analysis.

5. DISCUSSION

The graded evidence supports a bounded set of conclusions. IoT- and AI-enabled monitoring has the strongest convergent evidence in the corpus, while digital twins/BIM, immersive technologies, and nanotechnology remain less mature. The 18–22% and 58–70% figures are single-case findings and should not be interpreted as general technology effects. The evidence therefore supports prioritising scalable monitoring and predictive applications while treating higher-cost or less mature technologies as context-dependent investments.

For Nigeria, the implication is not that globally better-supported technologies should be adopted uncritically. Rather, adoption should be phased according to infrastructure, skills, maintenance, governance, cybersecurity, and regulatory readiness. Read as an indicative, author-judgment proposition rather than as validated guidance, the conceptual framework in Table 8 suggests that IoT/AI monitoring may offer the most accessible near-term entry point, provided governance and cybersecurity measures develop alongside deployment; this reading should be treated as a hypothesis for empirical testing, not as an established prioritisation.

The oil and gas evidence carries a parallel, similarly bounded implication for the Niger Delta context. Offshore and onshore drilling safety advances, spill-prediction models, automated safety protocols, and emissions-control measures including flare-gas recovery, address categories of environmental harm that have historically defined Nigeria's upstream environmental challenges (Alamutu, 2025; Akerele et al., 2024). The inherently safer design (ISD) framework's reported 58–70% safety improvement (Di Martino et al., 2021) illustrates the scale of improvement that engineering-controls-first approaches can plausibly achieve relative to administrative controls or PPE-led interventions alone, consistent with broader process-industry evidence that combining engineering controls, administrative controls, PPE, and behavioural interventions outperforms any single intervention type (Benson et al., 2023), but the specific 58–70% figure itself remains a single-case artefact that should inform expectations only qualitatively, not quantitatively.

The review's risk categories are particularly relevant to Nigerian implementation. Responsible-development principles should accompany deployment so that technologies introduced to improve

safety do not create new occupational, privacy, cybersecurity, or environmental risks. AI and IoT systems require data governance and cyber controls; nanomaterials require exposure and life-cycle safeguards; and digital twins require reliable infrastructure and technical skills. These are governance conditions, not findings measured in Nigeria.

This review's limitations, detailed in full in Section 3.6, bear directly on how its findings should be used. As a single-analyst, platform-assisted synthesis of secondary sources without a formal quality-appraisal instrument, it inherits real reproducibility constraints. The Nigerian policy implications drawn here are, without exception, extrapolations from global evidence rather than findings validated within Nigeria itself, and the framework in Table 8 should be read as a proposed research and investment agenda awaiting empirical testing, not as a confirmed characterisation of Nigerian conditions.

6. CONCLUSIONS

This review synthesised 37 verified peer-reviewed studies on emerging technologies for safety and environmental protection across construction, mining, and oil and gas engineering. Its contributions are threefold: a cross-sectoral evidence-graded map of six technology categories; an operationalised evidence-grading rubric with transparent limitations; and a twelve-dimension, explicitly indicative Nigerian adoption framework. The evidence is strongest for IoT- and AI-enabled monitoring and more limited for digital twins/BIM, immersive technologies, and nanotechnology. The review supports phased adoption of scalable monitoring and predictive technologies, accompanied by regulatory, cybersecurity, occupational-exposure, and workforce-development measures.

For policy, the findings support three concrete actions, each qualified by the review's evidentiary limits and by the conceptual, not empirically validated, status of the Table 8 framework from which the second and third actions draw: strengthening NESREA and sector-regulator capacity to evaluate emerging-technology deployments, guided by the regulatory-readiness gap identified in Table 8 rather than by the single-case quantitative figures reported in Section 4; incentivising phased, low-cost sensor and predictive-analytics adoption among small- and medium-scale mining and construction operators, as the technology category with both the strongest global safety evidence and, on the indicative framework's author-judgment ratings only, the most favourable near-term adoption profile; and establishing local occupational-exposure guidance for engineered nanomaterials ahead of, rather than after, wider deployment, given the unresolved global exposure-limit gap identified in Section 2.7. Each action should be piloted and revisited as the Table 8 ratings are empirically tested, rather than treated as settled by this review alone.

These contributions connect directly to ICESID 2026's conference theme, "Innovating Tomorrow: Harnessing Engineering to Drive Nigeria's Growth for Sustainable Development." The twelve-dimension adoption framework operationalises that theme at the level of individual technology-adoption decisions: it gives engineering practitioners and regulators a structured, if indicative, basis for harnessing globally emerging technologies in a manner calibrated to Nigeria's present infrastructure, skills, and regulatory conditions, rather than importing innovation agendas wholesale from better-resourced economies. In that sense, the framework's central proposition, that sustainable engineering-driven growth depends on matching technology adoption to demonstrated local readiness rather than to global technology maturity alone, is offered as a direct, if empirically provisional, contribution to the conference's growth-and-sustainability agenda for Nigerian engineering.

Priority future research includes empirical validation of the Table 8 framework under Nigerian mining, construction, and oil and gas conditions; longitudinal studies of worker-health outcomes for wearable and exoskeleton technologies; techno-economic evaluation of AI predictive-maintenance deployment; and locally grounded governance research on AI monitoring, privacy, and data protection. These studies would address the central limitation of the current literature: the shortage of Nigeria-specific empirical evidence on emerging technologies for safe and environmentally responsible engineering.

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