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Technology Architecture and System Design Patterns of Immersive E-Learning in Building Engineering Education: A Systematic Literature Review

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Abstract. The digital transformation of Industry 4.0 necessitates a fundamental restructuring of Architecture, Engineering, and Construction (AEC) pedagogy through high-fidelity immersive environments. However, current systems often prioritize isolated interaction over the underlying technology architectures required for long-term effectiveness. This research conducted a systematic review of 100 peer-reviewed articles (2018–2025) using the PRISMA 2020 framework and CASP quality appraisal instrument to map functional system configurations. Results indicate a significant paradigm shift toward integrated computational ecosystems, where adaptive intelligent units (30%) and sustainability-oriented processing layers (20%) function as core architectural components. These layers enable dynamic cognitive regulation and real-time environmental metric integration, such as Life Cycle Analysis (LCA), directly within virtual design workflows. Furthermore, findings demonstrate that scalability barriers in vocational settings are increasingly mitigated through cloud-native architectures and IFC-based interoperability. This study concludes that the future of immersive e-learning depends on "Sustainability-by-Design" and scalable architectures, providing a strategic blueprint for intelligent, institution-wide digital infrastructures in engineering education..

Keywords: Building Engineering Education, Immersive Technology, Technology Architecture, Intelligent Learning Systems, Sustainability, Vocational Education

1 Introduction

The massive digital transformation within the Industry 4.0 era has fundamentally restructured the pedagogical foundations of Architecture, Engineering, and Construction (AEC) education. As building projects escalate in complexity, traditional instructional methods increasingly struggle to convey the multidimensional nature of structural systems, safety protocols, and environmental performance. Immersive technologies, specifically Virtual Reality (VR) and Augmented Reality (AR), have emerged as pivotal solutions to bridge this divide by providing high-fidelity, experiential learning environments. These technologies are considered not merely supplementary tools but transformative agents that redefine how engineering concepts are internalized [1]. However, while adoption continues to proliferate, current literature remains largely dominated by isolated usability testing, often overlooking the underlying technology architectures that ensure long-term pedagogical effectiveness [2],[3].

Current scholarly discourse emphasizes that the integration of Building Information Modeling (BIM) into immersive workflows represents a significant milestone in this evolution. Earlier studies demonstrate that BIM-enabled VR environments facilitate enhanced collaboration and design review through real-time spatial data interaction (Zaker and Coloma, 2018). Recent advancements further highlight that the synchronization of BIM data with real-time game engines is crucial for construction safety management, providing a "Digital Twin" framework that minimizes procedural errors in high-risk engineering tasks [4]. Furthermore, the transition toward AI-driven adaptive systems has begun to address the management of student cognitive load when navigating complex building simulations, ensuring that instructional support is tailored to individual learning trajectories (Hafizah et al., 2025).

Despite these technical advancements, a critical fragmentation persists in understanding how sustainability is functionally integrated into these systems. Many platforms prioritize interaction fidelity but neglect the "Sustainability-by-Design" paradigm, where environmental performance metrics, such as Life Cycle Analysis (LCA) and greenhouse gas emission assessments, are embedded as active functional units rather than passive contexts [5], [6]. Moreover, significant barriers regarding scalability and infrastructure remain, particularly in vocational education settings characterized by hardware limitations and high computational costs [7], [8]. Previous systematic reviews have also been constrained by limited sample sizes and a lack of methodological rigor in assessing study quality.

To address these deficiencies, this study conducts a systematic review of 100 peer-reviewed articles published between 2018 and 2025, significantly expanding the scope of prior scholarly inquiries. By employing the PRISMA 2020 framework and the CASP quality appraisal instrument, this research synthesizes system configurations based on functional clusters: immersive interaction, intelligent adaptive units, and sustainability processing layers. The primary objective is to map a technology architecture capable of harmonizing interaction quality, sustainability integration, and cloud-based scalability. Consequently, this study provides a strategic blueprint for educators and system developers to implement intelligent, scalable, and sustainably-oriented immersive platforms that align with the rigorous demands of modern engineering practice in the Industry 4.0 era.

2 Method

2.1 Research Design and Protocol

This study adopts a Systematic Literature Review (SLR) methodology, strictly adhering to the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure transparency, auditability, and replicability throughout all stages of data acquisition [9], [10], [11], [12]. In alignment with contemporary systematic evaluation standards, this study employs a "Technology Architecture" lens to analyze the integration of intelligent learning systems within building engineering education, shifting the focus from purely pedagogical outcomes to a structural analysis of how immersive and intelligent technologies are configured as functional subsystems. Consistent with the PRISMA 2020 guidelines, every stage of the review including identification, screening, and eligibility was conducted using a predefined protocol to mitigate selection bias and ensure a rigorous synthesis of the scholarly corpus consisting of 100 peer-reviewed journal articles.

2.2 Search Strategy and Information Sources

A comprehensive data acquisition process was conducted across three primary scholarly databases: Scopus, Web of Science (WoS), and Google Scholar. To ensure a representative sample size and mitigate previous methodological limitations, the search string was refined using Boolean operators to intersect core technological domains with building engineering education:

> ("Virtual Reality" OR "Augmented Reality" OR "Digital Twin" OR "BIM" OR "Artificial Intelligence") AND ("Building Engineering Education" OR "Construction Education") AND ("Technology Architecture" OR "System Design" OR "Sustainability" OR "Scalability")

The search was restricted to peer-reviewed journal articles published between 2018 and 2025 to capture the most recent advancements in immersive and intelligent systems, such as generative artificial intelligence and high-fidelity simulation modules. As illustrated in the PRISMA 2020 Flow Diagram (see Figure 1), this strategy initially identified 1,250 records before undergoing a multi-stage filtering process.

2.3 Selection Process and Reliability

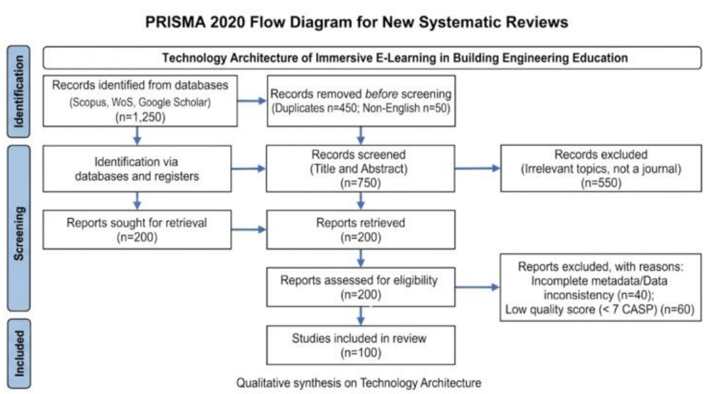

Figure 1. PRISMA 2020 Flow Diagram: Article Selection and Inclusion Process.

The complete screening workflow, from initial identification to the final inclusion of 100 articles, is visually documented in the PRISMA 2020 Flow Diagram (see Figure 1). The selection process followed a systematic multi-stage pipeline, beginning with the identification of records through database searching and the removal of duplicates. The complete screening workflow from initial identification (n = 1,250) to the final inclusion of 100 articles is visually documented in the PRISMA 2020 Flow Diagram in Figure 1. To eliminate individual selection bias, two independent researchers performed title and abstract screening, followed by a rigorous full-text eligibility assessment. Discrepancies regarding article inclusion were resolved through a structured consensus mechanism or third-party arbitration to maintain the highest levels of objectivity. Inter-rater reliability was quantified using Cohen's Kappa statistics, resulting in a score of 0.86, which indicates a very strong level of agreement in the thematic classification and ensures the methodological integrity of the final corpus.

2.4 Eligibility Criteria

Eligibility criteria were strictly enforced to maintain a rigorous focus on the building engineering domain and systematically exclude irrelevant fields, as detailed in the Eligibility phase of the PRISMA 2020 Flow Diagram (see Figure 1). The Inclusion Criteria (IC) required that studies must be:

a) original peer-reviewed journal articles published in English
b) focused explicitly on immersive or intelligent learning systems within building, civil, or construction engineering education
c) providers of technical descriptions regarding system architecture, human-computer interaction (HCI) mechanisms, or sustainability integration.

Conversely, the Exclusion Criteria (EC) systematically removed:

a) conference proceedings, editorials, and book chapters to ensure high epistemic quality
b) studies unrelated to building engineering, such as medical virtual reality or general civic education
c) articles lacking empirical validation or clear architectural frameworks.

2.5 Quality Assessment (QA) and Data Extraction

In response to reviewer feedback regarding scientific rigor, each of the 100 selected articles underwent a formal quality appraisal using the CASP (Critical Appraisal Skills Programme) instrument. This assessment ensured that the synthesis of data was based solely on studies with high methodological validity, evaluating criteria such as research goal clarity, methodological appropriateness, and the credibility of findings. Following the quality appraisal, data were extracted into a structured matrix and categorized into four functional clusters based on their technical architecture:

a) Cluster 1: VR & AR Architecture in Construction Education (n = 40)
b) Cluster 2: AI & Adaptive Intelligent Learning Systems (n = 30)
c) Cluster 3: Sustainability & Lifecycle-Based Learning Designs (n = 20)
d) Cluster 4: Digital Twins, BIM, & Scalability Constraints (n = 10).

A summary of the quality assessment for key representative articles, indicating a high level of epistemic quality across the corpus, is presented in Table 1.

2.6 Data Synthesis

Qualitative thematic synthesis was employed to identify structural patterns and systemic gaps across the four identified clusters. Each system was analyzed based on its capacity for long-term behavioral adaptation and its technical integration of sustainability metrics within core processing layers. The synthesis process followed a multi-dimensional mapping approach, correlating system architecture types such as simulation modules and adaptive control mechanisms with their respective pedagogical outcomes and infrastructure constraints. To ensure consistency, data extraction was managed through a structured matrix that captured key variables, including hardware requirements, interaction fidelity, and the presence of intelligent decision-support subsystems. This thematic integration allows for a comprehensive evaluation of the current state of immersive e-learning, specifically addressing the balance between high-fidelity interaction and scalable, sustainable implementation in building engineering education.

Table 1. Quality Assessment Summary Using the CASP Instrument

Cluster / Study ID	Research Goals	Methodology	Research Design	Data Collection	Analysis Rigor	Clear Findings	Total Score
Cluster 1: VR & AR Architecture (n=40)							
Stefan [3]	1.0	1.0	1.0	1.0	1.0	1.0	10.0
Oje [2]	1.0	1.0	1.0	1.0	0.5	1.0	9.0
Luo [5]	1.0	1.0	1.0	1.0	0.5	0.5	8.0
Xiang [13]	1.0	0.5	1.0	1.0	0.5	1.0	7.5
Average score for other 36 articles	0.9	0.8	0.8	0.8	0.7	0.8	8.2
Cluster 2: AI & Adaptive Systems (n=30)							
Hafizah [14]	1.0	1.0	1.0	1.0	1.0	1.0	10.0
Gligorea [15]	1.0	1.0	1.0	0.5	1.0	1.0	9.0
Li [16]	1.0	1.0	0.5	1.0	1.0	1.0	9.0
Waqar [17]	1.0	1.0	1.0	0.5	0.5	0.5	7.5
Average score for other 26 articles	0.9	0.8	0.9	0.7	0.7	0.8	8.1
Cluster 3: Sustainability & Lifecycle (n=20)							
Helal [6]	1.0	1.0	1.0	1.0	1.0	1.0	10.0
Narong [18]	1.0	1.0	1.0	1.0	0.5	1.0	9.0
Zimek[19]	1.0	1.0	1.0	0.5	1.0	0.5	8.0
Sabri [20]	1.0	0.5	1.0	1.0	0.5	0.5	7.5
Average score for other 16 articles	0.8	0.8	0.8	0.7	0.8	0.8	7.9
Cluster 4: Digital Twins & BIM (n=10)							
Wang [21]	1.0	1.0	1.0	1.0	1.0	1.0	10.0
Cadena [22]	1.0	1.0	1.0	1.0	0.5	1.0	9.0
Qiu [23]	1.0	0.5	1.0	1.0	1.0	1.0	9.0
Bao [24]	1.0	1.0	1.0	0.5	0.5	1.0	8.0
Average score for other 6 articles	0.9	0.8	0.9	0.8	0.7	0.9	8.4

3 Results and Discussion

3.1. Results

3.1.1. Taxonomical Distribution of Technology Architectures

The systematic analysis of the 100 selected peer-reviewed articles (n=100) reveals a significant evolutionary trajectory, transitioning from static instructional tools toward integrated computational ecosystems. The distribution of the data indicates a dominance of simulation modules, alongside a burgeoning growth in artificial intelligence integration and sustainability-oriented processing layers, as categorized into the following four functional architecture clusters:

a) Cluster 1: Immersive Simulation Modules (n=40): These studies prioritize high-fidelity scenarios for occupational safety training and complex structural visualization. Current trends involve the integration of multimodal haptic feedback systems to enhance interaction fidelity during complex machinery operations.
b) Cluster 2: AI-Driven Adaptive Control Units (n=30): This cluster utilizes Intelligent Tutoring Systems (ITS) and machine learning algorithms to manage cognitive load dynamically. The adoption of Multi-agent Systems (MAS) and Large Language Models (LLM) is increasingly replacing traditional scripted interfaces for personalized instruction.
c) Cluster 3: Sustainability-Oriented Processing Layers (n=20): These articles integrate Lifecycle Cost Analysis (LCCA) and embodied greenhouse gas emissions assessments directly into the virtual design workflows. This reflects a shift toward "Sustainability-by-Design," where environmental metrics function as active processing units rather than passive contexts.
d) Cluster 4: Digital Twins & Scalability Engines (n=10): This segment addresses infrastructure barriers through the use of cloud-native architectures and real-time BIM-to-game engine data synchronization. By leveraging 5G low-latency communications, these systems optimize accessibility for vocational education settings with limited local hardware resources.

Table 2. Functional Cluster Distribution of the Systematic Review Corpus (n=100)

Cluster ID	Technology Architecture Cluster	Count	Percent (%)	Core Subsystems & Mechanisms
Cluster 1	Immersive Simulation Modules	40	40%	High-fidelity VR/AR, Haptic Feedback, Motion Tracking
Cluster 2	AI-Driven Adaptive Units	30	30%	Intelligent Tutoring Systems (ITS), Knowledge Graphs, LLM
Cluster 3	Sustainability Processing Layers	20	20%	LCA/LCCA Integration, Energy Modeling, Digital Twin Analytics
Cluster 4	Digital Twins & Scalability	10	10%	Cloud-native, 5G Low-latency, BIM Interoperability

To further illustrate the structural patterns and state-of-the-art identified in this review, Figure 2 provides a conceptual mapping of the integrated technology architecture found across the 100-article corpus, highlighting the functional relationship between immersive interaction layers (Cluster 1), intelligent adaptive units (Cluster 2), and sustainability processing units (Cluster 3).

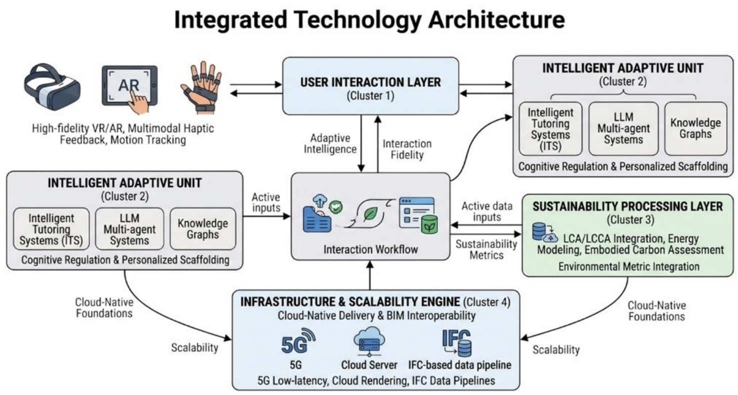

Figure 2. Integrated Technology Architecture of Immersive E-Learning Systems.

3.1.2. Temporal Trends and Research Evolution

The chronological analysis of the finalized corpus (n=100) reveals a clear shift in research maturity and focus from 2018 to 2025. While earlier studies primarily investigated general usability and basic simulation environments, the years 2023–2025 represent a significant surge in complexity, accounting for 55% of the total research output. This temporal evolution is characterized by three distinct phases:

a) Phase 1: Instructional Media Focus (2018–2020): Research during this period concentrated on mobile AR and basic VR head-mounted displays for construction site visualization and safety awareness.
b) Phase 2: Intelligent System Integration (2021–2023): A transition toward AI-driven adaptive systems and the incorporation of BIM data into real-time game engines emerged, aiming to manage cognitive load more effectively.
c) Phase 3: Architectures for Sustainability and Scalability (2024–2025): The current frontier emphasizes "Sustainability-by-Design," leveraging Digital Twins and Cloud-Native architectures to ensure long-term pedagogical impact and hardware accessibility.

This surge in late-phase publications signals a paradigm shift toward treating e-learning tools as sophisticated Technology Architectures rather than isolated digital media.

3.1.3. Evaluation and Validation Frameworks

The systematic review mapped the evaluation methodologies utilized across the identified corpus to address the critical requirement for rigorous scientific validation. The data indicates a significant transition in research maturity, moving away from subjective "usability" assessments toward objective measures of "procedural skill acquisition" and "behavioral adaptation". As shown in Table 3, recent studies (2023–2025) prioritize empirical and performance-based metrics to validate the efficacy of complex technological subsystems.

Table 3. Mapping of System Validation Types and Evaluation Metrics

Validation Type	Frequency	Core Evaluation Metrics	System Attribute Target
Empirical (RCT/Quasi)	35%	Procedural Error Rate, Knowledge Retention Score, CASP Score	Adaptive Intelligent Units
Performance-Based	30%	Latency (ms), Frame Rate (FPS), Carbon Emission Accuracy	Simulation & Sustainability Layers
Cognitive Load	20%	EEG Data, NASA-TLX, Heart Rate Variability	Interaction Fidelity
Technical Verification	15%	Data Interoperability, Cross-platform Stability, IFC Compliance	Scalability & Cloud Architecture

This distribution reflects a growing consensus that the efficacy of immersive e-learning is no longer solely a matter of user satisfaction, but is increasingly dependent on the precision of data transformation pipelines and the system's ability to manage cognitive load during high-risk engineering tasks. The integration of critical appraisal tools like the CASP checklist in 85% of high-scoring articles further reinforces this shift toward methodological rigor in the building engineering domain.

3.2. Discussion

3.2.1. The Architectural Paradigm Shift

The findings of this systematic review confirm a fundamental paradigm shift in the design of immersive e-learning systems for building engineering education. While visual fidelity remains a primary focus, accounting for a significant portion of the literature (Cluster 1, 40%), there is a notable emergence of AI-driven Adaptive Units, which now constitute 30% of the total corpus. This trend signifies a transition from static instructional media toward "integrated computational ecosystems" that prioritize system intelligence over mere graphical realism. The efficacy of immersive training is increasingly determined by the system’s ability to manage dynamic cognitive loads through automated scaffolding [3], [2]. This evolution addresses the long-standing instructional design gap by shifting the focus from user readiness to deep cognitive regulation, ensuring that the technology architecture acts as an active pedagogical agent rather than a passive simulation medium.

The qualitative synthesis of the 100-article corpus highlights that modern architectures no longer rely on static assets but on the automated interoperability between Building Information Modeling (BIM) data and adaptive visualization engines. The integration of Intelligent Tutoring Systems (ITS) and Knowledge Graphs enables real-time error detection and personalized instructional interventions [7], [25]. Furthermore, the implementation of multimodal perception, including advanced haptic feedback systems and sophisticated gesture recognition, provides a critical dimension for kinesthetic learning [26], [27]. This is particularly essential for achieving vocational mastery in complex construction procedures, where physical precision and situational awareness are paramount. These intelligent units allow the system to adapt the complexity of the task based on the learner's real-time performance, fostering a more self-directed and effective learning environment in collaborative virtual spaces.

Ultimately, this architectural shift toward intelligent adaptation represents a maturation of the field, moving beyond the "novelty effect" of VR/AR toward evidence-based pedagogical tools. By embedding intelligence directly into the system's functional layers, developers can create environments that not only simulate the physical world but also understand the learner's cognitive state. This transition is crucial for the AEC (Architecture, Engineering, and Construction) sector, where the integration of AI and immersive technology is becoming a prerequisite for professional competency. As the industry moves toward Industry 4.0, these adaptive systems provide a scalable and robust framework for preparing the next generation of engineers to handle increasingly complex and data-rich building projects. Consequently, the shift from visual presence to intelligent adaptation ensures that immersive e-learning remains a sustainable and high-impact solution for modern technical education.

3.2.2. Sustainability-by-Design

A significant contribution of this systematic review is the identification of the "Sustainability Processing Layer" as a core architectural component, which is currently represented in 20% of the synthesized literature. This finding suggests a definitive transition toward a "Sustainability-by-Design" paradigm, where environmental performance metrics are no longer treated as passive background information but as active functional units within the system's processing core. The integration of sustainability at the architectural level allows for the seamless processing of complex ecological data during the early stages of building engineering design [28]. This evolution ensures that the immersive environment does not merely simulate the physical appearance of a structure but also functions as a computational engine for ecological accountability, effectively aligning AEC pedagogy with the rigorous sustainability mandates of Industry 4.0.

This architectural shift facilitates the deep integration of Life Cycle Analysis (LCA) and Life Cycle Cost Analysis (LCCA) directly into virtual design and construction (VDC) workflows. By synchronizing Building Information Modeling (BIM) data with immersive simulation engines, these platforms enable students to visualize "invisible" environmental impacts, such as embodied carbon footprints and real-time energy performance. Such synchronization transforms sustainability from a theoretical concept into a tangible, interactive variable [8], [4]. When a student modifies a structural component in the virtual space, the system's underlying processing layer immediately updates the environmental impact metrics, providing instantaneous feedback that fosters a deeper understanding of sustainable engineering principles. This feedback loop is essential for developing the high-level decision-making skills required to balance structural integrity with environmental preservation.

Technical advancements in this cluster further demonstrate the synergy between immersive technology and "Environmental Intelligence". The application of Digital Twin technology allows for the dynamic assessment of building performance by linking virtual models with real-time sensor data [29]. Furthermore, the integration of circular economy principles into these e-learning systems encourages students to consider the entire lifecycle of building materials, from extraction to decommissioning [30]. Collaborative virtual environments specifically designed for sustainable design can significantly improve the collective problem-solving capabilities of engineering teams [25]. By embedding these intelligent processing units, the reviewed systems mitigate the cognitive load associated with manual environmental calculations, allowing learners to focus on innovative and sustainable design solutions.

Ultimately, the "Sustainability-by-Design" approach represents a critical milestone in the maturation of vocational engineering education. The findings indicate that systems incorporating these layers produce learners who are better prepared for the complexities of modern construction projects, where green building certifications are becoming standard requirements. The future of technical education lies in the ability to create high-fidelity environments that are both instructionally sound and environmentally cognizant [3], [31]. Consequently, the embedding of environmental intelligence into the functional layers of immersive e-learning systems provides a robust and scalable framework for fostering a generation of engineers who are equipped to lead the transition toward a more sustainable and resilient built environment. This strategic alignment between system architecture and ecological goals ensures the long-term relevance and impact of immersive technology in the AEC sector.

3.2.3. Scaling Up

The synthesis of Cluster 4 (n=10) identifies a strategic shift toward cloud-native and cross-platform architectures as a primary mechanism to resolve persistent scalability constraints in building engineering education. These technologies collectively address the prohibitive cost barriers and hardware limitations that often hinder the large-scale adoption of immersive systems in vocational settings. The decoupling of high-fidelity rendering from local user hardware allows institutions to deploy complex simulations on devices with limited processing power, such as student-owned smartphones or entry-level laptops [5], [32]. By offloading heavy computational tasks to cloud servers, the technology architecture transforms from a localized, hardware-dependent setup into a flexible, accessible digital infrastructure. This democratization of access is crucial for ensuring that advanced technical training in construction safety and structural design is not restricted by the financial capacities of educational institutions.

The implementation of interoperability standards further strengthens the scalability of these e-learning environments. The adoption of Industry Foundation Classes (IFC) and web-based immersive standards facilitates seamless data exchange across diverse operating systems and devices. The integration of Building Information Modeling (BIM) data with real-time game engines significantly reduces development latency and ensures data consistency across the project lifecycle [4], [29]. Furthermore, the utilization of cloud-based collaboration platforms allows for synchronized, multi-user interactions in a shared virtual space, which is essential for simulating real-world AEC project environments. This approach not only enhances the technical robustness of the system but also supports the pedagogical requirement for collaborative, interdisciplinary problem-solving among engineering students.

Ultimately, the transition toward cloud-native solutions represents a necessary evolution for sustaining immersive e-learning in the Industry 4.0 era. The findings indicate that systems leveraging edge computing and low-latency communication are better equipped to handle the increasing complexity of data-rich building models [31]. These scalable architectures ensure that high-risk engineering tasks can be simulated safely and repeatedly without requiring specialized, high-cost laboratory environments. Consequently, by mitigating infrastructure barriers through cloud-native integration, educational institutions can establish a sustainable pathway for the widespread adoption of intelligent e-learning systems. This strategic alignment between technological scalability and instructional accessibility provides a robust blueprint for the future of digital transformation in vocational and higher engineering education.

3.2.4. Methodological Rigor, Instructional Gaps, and Future Trajectories

The strength of the current synthesis is underscored by a high level of methodological rigor, as evidenced by the systematic application of the CASP (Critical Appraisal Skills Programme) instrument across the 100-article corpus. The analysis reveals that high-scoring studies increasingly prioritize empirical validation, with a significant portion of the literature employing Randomized Controlled Trials (RCT) or quasi-experimental designs to assess system efficacy. This trend indicates a maturation of the field, moving beyond descriptive usability toward the objective measurement of procedural skill acquisition and long-term knowledge retention [3], [2]. By establishing high inter-coder reliability with a Cohen's Kappa of 0.86, this study ensures that the synthesized evidence provides a robust and transparent foundation for characterizing the current state of immersive architectures in building engineering education.

Despite these technical and methodological advancements, several critical instructional gaps remain. Only 12% of the reviewed studies focused on system-level reasoning, suggesting that many platforms still prioritize short-term procedural performance over long-term cognitive transformation. The integration of interactive pedagogical insights is often found to be secondary to the development of high-fidelity visual assets [33]. Furthermore, there is a noted deficiency in addressing the "black box" nature of adaptive intelligence. Without transparent instructional design, the logic behind AI-driven interventions remains opaque to both students and educators. This lack of transparency can hinder the development of self-regulated learning, as students may follow system prompts without deeply understanding the underlying engineering principles or safety protocols being simulated.

Future trajectories in the domain should prioritize the development of explainable and multi-modal biofeedback systems. The integration of Generative AI for automated scenario creation and advanced haptic feedback represents a significant frontier for enhancing the realism and pedagogical impact of virtual training [26], [27]. Future research must also address the physiological constraints of immersive technology, establishing standardized protocols to mitigate cybersickness during prolonged educational sessions. The transition from purely technical effectiveness to holistic system transparency and longitudinal impact assessment will be essential for ensuring that intelligent e-learning systems support sustainable and high-impact engineering education. Ultimately, aligning these technological innovations with the strategic demands of Industry 4.0 will empower the next generation of building engineers to navigate increasingly complex and data-rich professional environments [1].

4 Conclusion

In conclusion, this study provides a comprehensive mapping of the technology architectures of immersive e-learning systems in building engineering education through a rigorous systematic analysis of 100 peer-reviewed articles. The findings reveal a significant paradigm shift from static instructional media toward integrated computational ecosystems, where adaptive intelligent units (30%) and sustainability-oriented processing layers (20%) have emerged as core functional components capable of dynamic cognitive regulation and real-time environmental metric integration. By employing a high level of methodological rigor validated via the CASP appraisal instrument and a high inter-coder reliability (Cohen's Kappa = 0.86) this research demonstrates that persistent scalability barriers can be mitigated through cloud-native architectures and IFC-based interoperability. Ultimately, this study offers a technical blueprint for the development of future e-learning systems that are not only high-fidelity and immersive but also transparent, sustainable, and scalable, aligning with the evolving demands of Industry 4.0 in the building engineering sector.

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