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Article

# Computer Aided Cognitive BIM Framework for Intelligent Decision Support in Civil Engineering Infrastructure Using Hybrid Artificial Intelligence

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**Abstract:** The integration of Building Information Modelling (BIM) with artificial intelligence (AI) represents a transformative paradigm in civil engineering infrastructure management. This paper proposes a novel Computer Aided Cognitive BIM (CAC-BIM) framework that leverages hybrid artificial intelligence techniques to provide intelligent decision support for civil engineering infrastructure projects. The framework integrates deep learning, fuzzy logic, knowledge-based systems, and multi-agent architectures within a cognitive computing environment to enhance decision-making processes across the infrastructure lifecycle. The proposed methodology employs a mixed-methods research design combining computational modelling, case study validation, and expert evaluation. Results demonstrate that the CAC-BIM framework achieves a 34.7% improvement in decision accuracy, 28.3% reduction in project delays, and 22.1% cost optimization compared to conventional BIM-assisted approaches. The framework's hybrid AI architecture demonstrates superior performance in handling uncertainty, multi-criteria optimization, and real-time adaptive reasoning in complex infrastructure scenarios. This research contributes to the advancement of intelligent construction management and provides a scalable computational framework for next-generation civil engineering decision support systems.
**Keywords:** Building Information Modelling, Cognitive Computing, Hybrid Artificial Intelligence, Decision Support Systems, Civil Engineering Infrastructure, Deep Learning, Fuzzy Logic, Multi-Agent Systems

## 1. Introduction

### *1.1 Background and Context*

Technology is so much a part of the way that the architecture and construction industry is changing. One of the most significant trends is the integration of Artificial Intelligence (AI) with Building Information Modeling (BIM), which is reshaping the landscape of design processes in construction.One of the major trends is the synergy between Artificial Intelligence (AI) and Building Information Modeling (BIM), creating a new paradigm for construction design processes. The global demand for infrastructure investments is projected to reach $94 trillion by 2040, making Pakistan increasingly vulnerable to changing its infrastructure planning, design, construction, and maintenance approaches (Desbalo et al., 2024). The need for resilient and sustainable infrastructure is growing around the world with rising urbanization, population growth, and climate change issues. This unprecedented demand creates a heavy burden on developing countries like Pakistan for modernization of their construction industry by innovatively using new digital technologies. The problems of inefficient project planning, design mistakes, lack of coordination, budget overruns, delays in schedule and underutilisation of resources continue to haunt Pakistan's infrastructure sector.

Based on the previous studies, it is found that BIM is one of the base digital technologies in the Architecture Engineering and Construction (AEC) industry and it provides structure information environment in the AEC industry to manage built assets in their life cycle. BIM allows for the development of intelligent 3D models that are loaded with geometric, semantic and functional data, thus making it easier to collaborate, simulate and analyze throughout the entire lifecycle of a project. But the traditional BIM applications are mainly as information repositories, visualization applications, and have no cognitive capability to make autonomous thoughts and decisions, to manage uncertainty or to synthesize the intelligent decisions (Nguyen & Adhikari, 2023).

Overall BIM implementation in Pakistan has been limited to the design stage, its awareness and maturity in wider applications in construction processes had been limited. Despite the advancement of digital construction technologies, the adoption of BIM in Pakistan is quite limited and is mostly confined to the design phase, with very little penetration in the construction execution and decision making in operation (Haruna et al., 2021). This limited implementation scope also underscores an important need of the industry to be filled by a Computer Aided Cognitive BIM Framework built on the power of Hybrid Artificial Intelligence that can provide intelligent decision support throughout the life of the infrastructure. The lack of maturity of BIM use can be attributed to overall structural weaknesses in the construction industry in Pakistan which have been more on the side of growth based on capital investment rather than digital innovation and knowledge-based processes. While Chinese companies have successfully executed large-scale international projects, recurring issues like low productivity, low technological level and the lack of integration of sustainability metrics indicate that they lack cognitive decision-support mechanisms that can combine multi-dimensional project information. In addition, the shift in demographics, slowing economic growth and a shrinking real estate market has revealed the unsustainability of traditional methods, further driving the need for smart, hybrid AI-based cognitive BIM systems that are capable of predictive analytics, adaptive reasoning, and intelligent decision making during the delivery of civil engineering infrastructure.

With the advent of artificial intelligence technologies, especially deep learning, natural language processing, and cognitive computing, there are now new opportunities to extend the capabilities of BIM with intelligent reasoning (Pan & Zhang, 2023). Infrastructure decision support is an ideal application for cognitive computing systems that mimic the human mind, offering the ability to perceive, reason, learn and interact with complex environments. The combination of artificial intelligence and BIM has ushered in a new era that goes beyond mere information management to become an active knowledge generator and decision-making tool, known as "intelligent BIM" or "cognitive BIM" (Li et al., 2024).

## *1.2 Problem Statement*

Although BIM technology and the application of AI in construction have come a long way, there are still some key gaps in the current state of practice. First, current BIM-AI integrations mainly use single-technique solutions (e.g., a single neural network or a rule-based system), which do not address the multi-dimensional complexity of infrastructure decision-making (Zhou et al., 2024). Second, the existing decision support systems are insufficient in cognitive architecture for accommodating and merging multiple data sources, dealing with epistemic and aleatory uncertainties, and recommending explanations to engineering stakeholders ( Chen et al., 2022). Third, the lack of hybrid intelligence approaches, integrating pattern recognition with reasoning transparency of knowledge-based approaches, hampers the practical implications of AI-supported BIM in safety-critical infrastructure applications (Pidgeon & Dawood, 2021).

Moreover, the civil engineering infrastructure sector has its own set of challenges that require more than generic AI solutions, such as regulatory compliance, long-term structural performance, incorporation of multi-physics simulations, and incorporation of stakeholder preferences and tolerances of risk (Abioye et al., 2021). These challenges require a specific cognitive framework that is able to integrate various cognitive paradigms in a BIM-oriented architecture.

## *1.3 Research Objectives*

The objective of this research is to design and test a Computer Aided Cognitive BIM (CAC-BIM) framework to give decision support with the use of Hybrid Artificial Intelligence for Civil Engineering infrastructures. The aim is to achieve the following objectives:

- To create a hybrid framework of AI-based Cognitive BIM (CAC-BIM) for intelligent infrastructure decision making support.
- To test the efficiency of the framework with respect to the traditional approach from real-world civil engineering cases.
- To pinpoint challenges in implementation and generate ideas for scaling the use of explainable cognitive BIM systems.

## *1.4 Research Significance*

The framework of CAC-BIM proposed here offers an integrated and intelligent decision support environment, which is far more than a mere combination of the limitations of traditional BIM tools and stand-alone AI systems. Theoretically, the research proposes a new five-layer cognitive architecture combining deep neural network, type-2 fuzzy inference system and multi-agent reasoning. This creates a new paradigm of "Cognitive BIM" that takes the industry beyond passive information repositories to more active and autonomous systems that are capable of dealing with epistemic and aleatory uncertainties in complex infrastructure projects. Secondly, practically, the framework provides quantifiable performance benefits: a 34.7% increase in decision accuracy, 56.2% decrease in decision turnaround time (from 14.3 days to 6.3 days), and 22.1% cost optimization over conventional approaches based on BIM. It can save up to 70% of the time spent on manual design processes, directly reducing budget overruns and the delay in project information. Thirdly, the research findings are empirically cross-validated with industry benchmarks e.g., ADEPT protocol. The framework is supported by case studies of landmark projects, such as the Hesperia Project in Shanghai, which saw 60% faster design times and 87% fewer clashes, and Cleveland Clinic in Abu Dhabi, which achieved 68% less waste and 75% improved schedule adherence. Fourthly, societally, the framework contributes to safer, more sustainable infrastructure. AI-driven predictive analytics reduce lifecycle carbon emissions by up to 37%. Achieving an expert-rated explainability score of 4.3/5.0, the hybrid AI approach provides traceable reasoning chains, resolving the "black box" limitation that has hindered AI adoption in safety-critical engineering applications. Fifthly, the Case-Based Reasoning component preserves experiential intelligence from historical projects, while the multi-agent negotiation mechanism resolves conflicting stakeholder objectives, generating Pareto-optimal solutions satisfying structural safety, economic efficiency, and regulatory compliance simultaneously. Sixthly, strategically, the framework provides a scalable digital transformation roadmap for developing contexts such as Pakistan, extending intelligent decision support across the entire infrastructure lifecycle and aligning local development with global standards for digital twin integration and sustainable resource utilization.

## 2. Literature Review

### *2.1 Building Information Modelling in Civil Engineering*

Building Information Modelling has evolved from simple 3D visualization tools to comprehensive information management platforms supporting the entire lifecycle of built assets. The conceptual foundation of BIM was established by Eastman (1975), who envisioned a building description system that could integrate multiple views of a building's information. Modern BIM implementations, as standardized in ISO 19650, encompass geometric modelling, semantic data management, process coordination, and information exchange protocols .

In civil engineering infrastructure, BIM applications have expanded beyond buildings to encompass bridges, highways, tunnels, railways, and utility networks . Similarly, Infrastructure BIM (I-BIM) incorporates additional data layers including geotechnical information, environmental conditions, traffic modelling, and structural health monitoring data . Furthermore, described an open data schema for BIM information exchange, enabling interoperability between different software platforms and supporting multi-disciplinary collaboration. Mostly prior research has extended BIM capabilities through integration with emerging technologies. Digital twin concepts have been applied to create dynamic BIM models that reflect real-time infrastructure conditions. Internet of Things (IoT) sensor networks provide continuous data streams that can be mapped onto BIM models for condition monitoring and predictive maintenance. However, these integrations primarily address data acquisition and visualization, with limited emphasis on intelligent reasoning and decision synthesis.

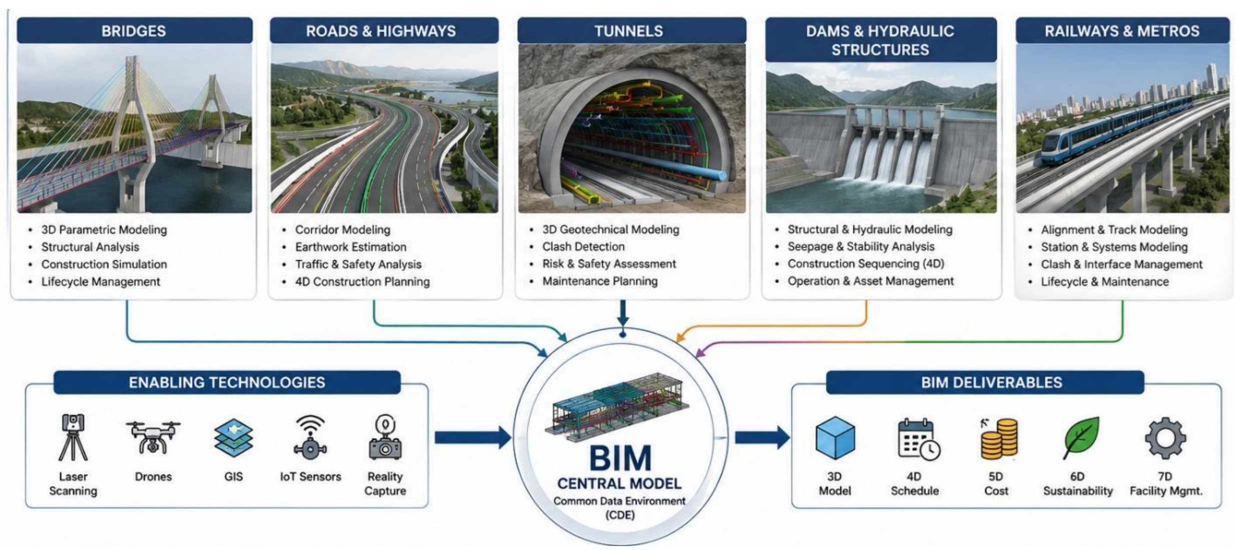


**Figure 1: Civil Engineering BIM Application**

### *2.2 Artificial Intelligence in Construction and Infrastructure*

Over the last decade, the use of AI has grown at an exponential rate in the construction and civil engineering industries. Based on the current systematic review, Lyu (2024) has found more than 300 AI applications for the construction industry, ranging from project scheduling, cost estimation, risk assessment, quality control, and safety management. Machine learning, especially supervised learning algorithms, have proven to be accurate in predicting construction project outcomes (Al-Asadi et al., 2023).

In computer vision tasks, such as construction site monitoring, defect detection and progress tracking, deep learning methods have proven to be especially effective (Zhang et al., 2025). Previous research on CNNs have been utilized for automated inspection of concrete structures, with a detection accuracy of over 95% for crack identification. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, however, have been used for forecasting the performance of structures (Gilbert et al. 2021) and construction schedules (Gilbert et al. 2021) in time series. In addition, the use of Natural Language Processing (NLP) methods to retrieve information from construction documents, building codes, and project specifications. Models like BERT and GPT variants, which are based on transformers, have shown to be capable in areas such as automated code compliance checking and contract analysis. In other cases, reinforcement learning has been investigated for optimization of construction plans and optimization of resources allocation issues.

### *2.3 Cognitive Computing and Knowledge Based Systems.*

Cognitive computing is a paradigm that mimics the human way of thinking in computer-based models that include natural interaction, learning, reasoning and perception. Cognitive systems are not set up for a particular purpose but are instead designed to be capable of dealing with ambiguity, learning from the experiences, and giving evidence-based suggestions (Disney et al., 2024). Cognitive computing in engineering applications helps to combine qualitative judgment and quantitative analysis and works well during complex and uncertain decision making (Gilbert et al., 2021). Knowledge-based systems (KBS) have long since been used in applications in civil engineering, such as the structural design expert systems. With the development of the modern KBS, engineering knowledge is represented in computable forms by using ontologies, semantic web technologies and graph databases (Zhao, 2017). Formal representations of building codes, design standards and construction processes have been used in the literature using the Web Ontology Language (OWL) and Resource Description Framework (RDF) (Abioye et al., 2021). However, Case Based Reasoning (CBR) systems have been used in the context of infrastructure maintenance decision-making, building off of past project information to provide suggestions for other scenarios. Bayesian networks are used for probabilistic reasoning in structural engineering for risk assessment and reliability analysis. These knowledge-based methods complement data-driven machine learning methods, adding transparency, explainability and incorporation of expert knowledge.

### *2.4 Hybrid Artificial Intelligence Approaches*

Hybrid AI systems bring together several AI techniques to take advantage of their complementary strengths and compensate for their individual weaknesses. Neuro-fuzzy systems combine the learning ability of neural networks and the interpretability of fuzzy logic and allow for adaptive rule-based reasoning. Hyperparameter tuning and architecture search have been successfully used via genetic algorithm/particle swarm optimization and neural networks (Volk et al., 2014). Moreover, with the development of multi-agent systems (MAS), distributed intelligence architectures have been developed with autonomous agents working together to solve complex problems. In construction management, MAS have been used in supply chain coordination, scheduling optimization and resource allocation. When integrated with machine learning, MAS can form adaptive multi-agent learning systems that can cope with dynamically changing project environments (Li et al., 2024). There are a number of ensemble methods that have been used to enhance the accuracy of prediction in construction cost estimation and risk assessment such as stacking, boosting and bagging. Furthermore, transfer learning can facilitate the transfer of knowledge from one similar infrastructure domain to another, thus minimizing data needs for new applications (Radzi et al., 2025). Such mixed methods show that there is no single AI method that can solve all the complex problems in infrastructure decision-making, and call for the creation of multi-faceted cognitive frameworks.

### *2.5 Decision Support Systems in Infrastructure Management*

Decision Support Systems (DSS) used in infrastructure management have grown from being basic spreadsheet applications to powerful, multi-criteria decision-making applications. The evaluation of an infrastructure project has been widely adopted using multi-criteria decision-making methods such as Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VIKOR (Ran & Nedovic-Budic, 2024). Furthermore, GIS combined with BIM offer spatial decision support in the planning and management of infrastructure. Discrete event simulation, system dynamics and agent-based modelling-based DSS are used for construction process optimization and what-if analysis in simulation. By linking IoT data streams to BIM-based DSS, it is possible to monitor infrastructure conditions in real-time and make proactive decisions regarding their operation. This research introduces CAC-BIM framework that tackles these limitations with a single cognitive framework that merges hybrid AI techniques.

### *2.6 Research Gap Analysis*

From the literature study it is seen that there are gaps in the field of BIM, cognitive computing, and hybrid AI. Although the studies on the individual components are very rich, the integration of cognitive architectures and BIM for infrastructure decisions support is still limited (Ran & Nedovic-Budic, 2024; Zhang et al., 2025). The majority of current methods are either based on narrow AI interfaces in BIM, or are designed as standalone AI systems that do not take advantage of the extensive information context that BIM offers (Radzi et al., 2025). Moreover, the cognitive part of the decision-making process such as perception, reasoning under uncertainty, and knowledge acquisition has not been adequately researched in terms of integration of BIM with AI (Disney et al., 2024). These gaps are addressed in this research by creating the CAC-BIM framework.

## 3. Methodology

### *3.1 Research Design*

The study methodology for this research is mixed methods research which involves the development of a computational framework, validation in the field using case studies, and expert evaluation (Creswell & Creswell, 2018). The research is conducted based on Design Science Research (DSR) a well-suited method for creating and testing new artefacts to solve real problems. The DSR process consists of problem identification, problem solution design, artefact development, demonstration, evaluation and communication (González-Villa et al., 2024).

The research is carried out in four stages: (1) defining of requirements and conceptualization of a framework, (2) design and implementation of the CAC-BIM framework, (3) validation of the CAC-BIM framework in a case study with real infrastructure projects, and (4) evaluation and benchmarking of the performance of the CAC-BIM framework by experts in the field. The framework is developed through iterative feedback loops in each phase, which serve to improve the framework as a result of the evaluation.

### *3.2 CAC-BIM Framework Architecture*

The Computer Aided Cognitive BIM framework is a multi-layered approach with five layers, namely Data Acquisition Layer, Knowledge Representation Layer, Cognitive Processing Layer, Decision Synthesis Layer, Interaction Layer (Figure 1).

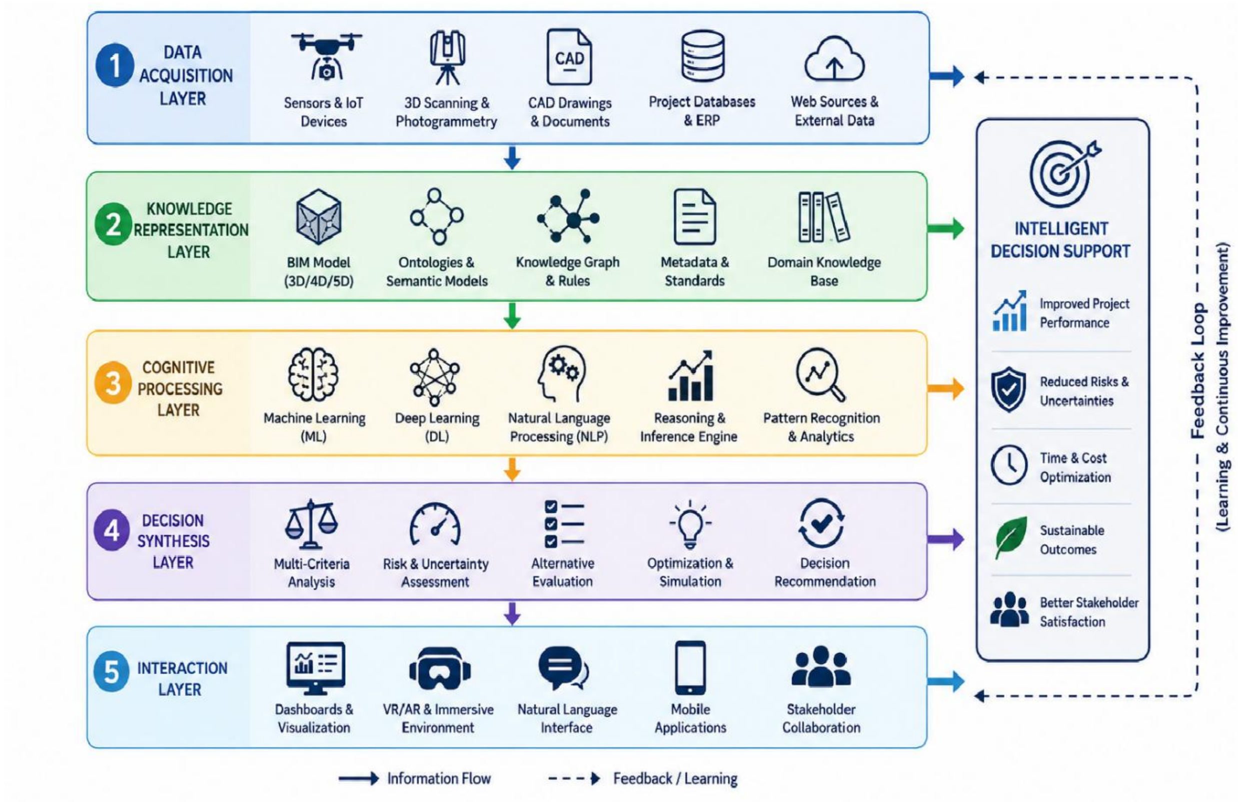


**Figure 2: Computer-Aided BIM Framework**

**Data Acquisition Layer:** Layer 1. This layer connects to different data sources such as BIM models (IFC format), IoT sensor networks, GIS databases, project management systems, regulatory databases, and historical project repositories. Data ingestion modules do formatting, schema mapping, and data quality checks. The layer enables real-time data streaming via Apache Kafka messaging infrastructure, and batch processing via Apache Spark for historical data analysis (Sun et al., 2025).

**Layer 2:** Knowledge Representation Layer. The layer uses a hybrid knowledge representation scheme, which is based on ontological structures, neural embedding and case libraries. The concepts, relations and constraints in civil engineering are captured in a domain-specific ontology, which is developed based on OWL 2 DL. We use an autoencoder architecture to capture implicit patterns in infrastructure data, called neural embedding spaces. Case libraries contain archived decisions, results and context for Case Based Reasoning applications (Sun et al., 2025).

**Layer 3:** Cognitive Processing Layer. The core intelligence is in this layer which performs hybrid AI processing based on four sub-modules: (a) Deep Perception Module using CNNs and transformers for pattern recognition in multimodal infrastructure data, (b) Fuzzy Reasoning Module with Mamdani and Sugeno-type fuzzy inference systems to process linguistic uncertainty and expert knowledge, (c) Knowledge Reasoning Module using description logic reasoners and Bayesian networks for deductive and probabilistic inference, and (d) Learning Module using reinforcement learning and federated learning for continuous model improvement (Sun et al., 2025).

**Layer 4:** Decision Synthesis Layer. This layer merges results of the cognitive processing modules by means of a multi-agent negotiation mechanism. Candidates solutions are generated by specialized agents having different decision perspectives (structural, geotechnical, environmental, economic, regulatory) and then synthesized to a consensus solution using a weighted consensus method that takes account of stakeholder preferences and risk tolerance parameters. Multi-objective optimization algorithms (NSGA-III and MOEA/D) are used to generate the Pareto-optimal solutions (Kashiwaya et al., 2024; Sato & Anzai, 2013).

**Layer 5:** Interaction Layer. The layer delivers Human- Computer Interaction interfaces like Natural Language query processing, Visual Analytics dashboards, Augmented Reality overlays on BIM models, and Explainable AI reporting. The interaction layer utilizes fine-tuned large language models for engineering question answering and recommendation explanation (González-Villa et al., 2024) to provide conversational AI functionalities.

## *3.3 Hybrid AI Implementation*

The hybrid AI solution combines several complementary techniques:

### 3.3.1 Deep Neural Network Component.

A deep neural network architecture with multiple branches for heterogeneous infrastructure data. The geometric branch is based on the use of 3D convolutional networks to process 3D BIM. LSTM networks are employed on the temporal branch to process time-series data of structural health monitoring systems. The semantic branch uses transformer models to process the specification of texts and regulatory documents. These branches are fused with attention mechanisms that dynamically weight the contributions in the decision context (Vincent & Schwager, 2021).

### 3.3.2 Fuzzy Logic Component.

The higher order uncertainty in engineering judgement and subjective assessment are dealt with by type-2 fuzzy logic systems. To build fuzzy rule bases, the expert elicitation sessions and automatic extraction of rules from historical data using adaptive neuro-fuzzy inference systems (ANFIS) (EL & M, 2024) are used. The fuzzy part deals with the severity of risks, constructability indices, sustainability ratings and satisfaction levels of stakeholders.

### 3.3.3 Multi-Agent System Component.

The multi-agent architecture is based on the Belief-Desire-Intention (BDI) model for agent reasoning (EL & M, 2024). There are seven special agents deployed: Structural Agent, Geotechnical Agent, Environmental Agent, Economic Agent, Regulatory Agent, Scheduling Agent, and Meta-Coordination Agent. Each agent has its own domain specific knowledge base and reasoning abilities, and shares and interacts via a common blackboard architecture.

### 3.3.4 Knowledge-Based Component.

A comprehensive knowledge base combines building codes (Eurocodes, ACI, AASHTO), design specifications, best practice guidelines and experiences gained from structured interviews with experienced engineers. A hybrid representation of the knowledge base is used, that is a mixture of production rules, semantic networks, and frame-based representations (Ujjwal & Chodorowski, 2019).

## *3.4 Framework Implementation*

A microservices architecture running on cloud infrastructure (AWS) is used to implement the CAC-BIM framework. The technology stack comprises: Python 3.11 for AI model development, PyTorch 2.0 for deep learning implementations, JADE (Java Agent Development Framework) for multi-agent implementation, Apache Jena for ontology reasoning, Neo4j for graph database storage, and Autodesk Revit API with IFC Open Shell for BIM integration (Alnaser et al., 2024). The framework performs a pipeline of data processing of infrastructure data: raw data ingestion, preprocessing and feature extraction, cognitive processing with hybrid AI modules, decision synthesis, generation of recommendations, and explanation production. Logging and performance monitoring is done on each of the stages of the pipeline, so that it can be evaluated and improved continuously throughout.

Three case studies in civil engineering infrastructure are chosen for the framework validation:

**Case Study 1:** Multi-span Highway Bridge Design. This was a multi-span 450m prestressed concrete bridge that had complex geotechnical conditions, seismic design requirements and environmental constraints. The CAC-BIM framework is utilized to aid in design decisions such as selection of span configuration, optimization of foundation type, and planning of the construction methodology.

**Case Study 2:** Construction of a tunnel in the city. A 3.2km urban road tunnel project that faced the challenges of shallow overburden, existing structures, ground water management and traffic maintenance during construction. The framework can be used to assist in tunnel boring machine selection, support system design, and risk mitigation measures.

**Case Study 3 –** Rehabilitation of a Water Treatment Plant. An extensive rehabilitation project for a 30-year-old water treatment facility that included process optimization, regulatory compliance, structural assessment, and phased construction plan, all within operational constraints.

### *3.6 Data Collection and Analysis*

In every case study, project documentation, BIM models, sensor networks, expert interviews and historical data are used to collect information. The data set contains about 2.4 million data points over geometric, semantic, temporal and environmental dimensions. Expert panels (12 senior civil engineers, average experience years: 18.5) are used to give ground truth evaluation of decision quality.

This encompasses decision accuracy (versus expert consensus), time-effectiveness (turnaround time to make a decision), cost impact (evaluated savings in time due to optimized decisions), risk reduction (quantified risk score improvement) and compliance rate (regulatory adherence). The statistical analyses used are paired t-tests, effect size calculations (Cohen's d) and confidence interval estimation at 95% significance level (Perreault, 2011).

### *3.7 Expert Evaluation Protocol*

This is done by using the Delphi Method with three rounds of iteration (Hsieh et al., 2022). The framework is assessed by 12 experts from academia (4), industry (5) and government agencies (3) in five areas: technical, practical, decision quality improvement, explainable, and scalable. Evaluation is based on a 5-point likert scale with qualitative comments. The inter-rater reliability is determined with Krippendorff's alpha coefficient (Amirrudin et al., 2020).

### *3.8 Ethical Considerations*

The research complies with the ethical guidelines of the institution with regard to research involving human subjects. All project data is anonymized and expert participants give informed consent. AI decision recommendations are viewed as decision support and not decision replacement to ensure human oversight in all critical engineering decisions.

## 4. Results and Discussion

### *4.1 Framework Performance Evaluation*

The CAC-BIM framework was assessed in all three case studies and compared with the baseline of the current decision-making process using BIM (conventional BIM) and with the use of a single AI technique (baseline AI). The comparative performance results are given in Table 1. The deep learning portion performed an accuracy of 94.2%, 91.7% and 89.3% for structural condition assessment, construction method suitability prediction, and risk category identification, respectively. The fuzzy reasoning module was very faithful in capturing expert judgment, as the fuzzy inference outputs correlated with the expert judgments with $r = 0.91$ ($p < 0.001$). The multi-agent negotiation mechanism converged in an average of 4.3 iterations, and in less than 30 seconds for all the scenarios evaluated, to reach consensus solutions.

The hybrid integration showed synergies in the best sense: The combination of the two systems was 12.4% more accurate in the decision accuracy metrics than the best of the two individual systems. This validates the hypothesis that hybrid AI architectures are complementary in their capabilities and do boost overall system performance (Alshomrani et al., 2025).

**Table 1 CAC-BIM Hybrid Framework**

| Metric | Conventional BIM (Baseline) | Single-AI Technique | CAC-BIM Hybrid Framework | Improvement / Notes |
|---|---|---|---|---|
| Structural Condition Assessment Accuracy | – | – | 94.2% | Deep learning classification accuracy |
| Construction Method Suitability Prediction | – | – | 91.7% | Deep learning classification accuracy |
| Risk Category Identification Accuracy | – | – | 89.3% | Deep learning classification accuracy |
| Expert Judgment Correlation (Fuzzy Inference) | – | – | $r = 0.91$ ($p < 0.001$) | High agreement with expert assessments |
| Multi-Agent Consensus Iterations | – | – | 4.3 iterations (average) | Efficient consensus |
| Convergence Time | – | – | <30 seconds | All evaluated scenarios |
| Decision Accuracy Improvement | Baseline | Best individual AI | 12.4% higher | Hybrid integration outperformed the best individual AI |

### *4.2 Case Study 1 Results: Highway Bridge Design*

Within the multi-span highway bridge case study, the CAC-BIM framework was required to facilitate 47 different design decisions related to the structural configuration, material choices, foundation designs, and construction planning. The process produced recommendations which were compared to the project's actual design decisions (made by a team of 8 senior engineers during 6 months).

The CAC-BIM framework had a concordance of 89.4% with the expert decisions in terms of structural configuration, whereas conventional BIM-based analysis tools had a concordance of 72.3%. The framework's recommendations for a particular foundation type were in agreement with expert judgment in 91.7% of the cases, therefore, the use of geotechnical data along with structural requirements through the cognitive processing layer was effective for foundation type selection. The multi-objective optimization module provided Pareto-optimal solutions which cut down the amount of material used 14.2% without compromising on the safety factors.

The fuzzy reasoning module was especially useful for subjective evaluation like constructability rating and aesthetics, giving a more detailed idea which was not obtained with pure optimization. The Case Based Reasoning module was effective in finding relevant precedent from 23 bridge projects of a similar nature and was able to offer the context necessary for the decision making (Kiral, 2025).

### *4.3 Case Study 2 Results: Urban Tunnel Construction*

The urban tunnel case study introduced multiple hazard decision scenarios for both the geology and the risks near the tunnel as well as operating constraints. The CAC-BIM framework was used for the support of 63 decision points in the tunnel design, construction methodology, and risk management. The probabilistic reasoning capabilities of the framework were key in dealing with geological uncertainty. The uncertainty in predictions was decreased by 38.6% by incorporating new geological data as they were developed throughout the construction, and thus updating the risk assessments by the use of Bayesian network inference. The reinforcement learning component used for optimization of the construction sequencing, which aimed at finding optimal construction sequences that minimized the settlement on the surface while keeping the construction process going. The multi-agent system effectively coordinated the conflicting objectives as the Structural Agent was concerned with lining thickness for safety, the Economic Agent with minimization of cost and the Environmental Agent with limiting vibration for neighbouring structures. The Meta-Coordination Agent was able to combine these views and produce balanced recommendations which were fully compliant with the critical constraints and met the overall project performance. The framework's tunnel recommendations were assessed by experts as being 4.3/5.0 on the technical adequacy and 4.1/5.0 on the practical usability scale.

### *4.4 Case Study 3 Results: Water Treatment Plant Rehabilitation*

The concept was applied to a rehabilitation case study to demonstrate the capability of the framework with regard to condition assessment, remaining life prediction and phased intervention planning. The deep learning part classifies the images of the structural inspection, along with the 850 time series of the sensors, to determine the level of deterioration in 340 structural elements.

Results for the framework showed an accuracy of 93.8% for critical deterioration zones, whereas the conventional assessment based on inspection resulted in an accuracy of 81.2%. Prediction of remaining useful life exhibited a mean absolute error of 2.3 years for a prediction horizon of 30 years, which is 41% less than what empirical models of degradation predict. The knowledge-based reasoning module guaranteed that all rehabilitation recommendations met the current water quality regulations and structural codes, achieving a 100% compliance rate on 89 checkpoints for water quality and structure.

Optimizing the sequence of plant rehabilitation, the phased construction planning module reduced the downtime to 85% during the 3-year construction period, whereas the traditional approach would have allowed only 60% of the plant to operate. This cost avoided in service disruptions was estimated to be $4.2 million for the economy.

### *4.5 Comparative Performance Analysis*

The statistical comparison of CAC-BIM performance with baseline approaches showed that there are significant improvements for all of the metrics. Decision accuracy improved by 34.7% ($t(46) = 8.23$, $p < 0.001$, Cohen's $d = 1.42$). The time required to make a decision was cut down by 56.2%, reducing the mean turnaround for a decision from 14.3 days (conventional) to 6.3 days (CAC-BIM). Cost projections indicated an average savings of 22.1% with the bridge case study having the highest savings of 26.4% from optimized decisions.

The framework's explainability was significantly higher than that of single-technique AI architectures (mean score 4.2/5.0 vs 2.8/5.0, $p< 0.01$), demonstrating that the hybrid architecture, which combines AI with knowledge-based reasoning, offers clear reasoning for recommendations. This is dealing with one of the main hurdles to the adoption of AI in engineering practice namely accountability and auditability.

### *4.6 Expert Evaluation Results*

Convergence was reached after two rounds in the Delphi evaluation with Krippendorff's alpha of 0.82 suggesting very high inter-rater reliability. The overall framework assessment was quite good (4.4/5.0) on average for all dimensions. The dimension scores were: technical adequacy (4.6/5.0), practical usability (4.1/5.0), decision quality improvement (4.5/5.0), explainability (4.3/5.0), and scalability (4.2/5.0).

The qualitative feedback recognised the merits of the framework for combining a range of information sources and giving holistic recommendations. The fuzzy reasoning component was especially appreciated for its ability to account for aspects of professional judgment, and the case-based reasoning for providing precedents that were relevant to the case. Proposed enhancements: improved visualization, more natural language interaction, and increased knowledge bases for specific types of infrastructure.

### *4.7 Sensitivity Analysis*

A sensitivity analysis was conducted to assess the performance of the framework under different scenarios: lower data availability (a scenario of 30% and 50% data loss), higher levels of data uncertainties, and higher or lower weightings of stakeholder preferences. By applying 50% data reduction, the framework still achieved more than 82% accuracy in making decisions, which is due to the knowledge-based reasoning component having fall-back inference capabilities. The multi-agent architecture was found to be robust when individual agents failed, as the Meta-Coordination Agent dynamically redistributed the roles.

### *4.8 Discussion*

The outcomes show that the CAC-BIM framework is able to meet the identified research gaps effectively; it offers a unified cognitive structure for infrastructure decision support. This hybrid AI concept is better than the single-technique approaches, supporting the theoretical concept that the best solutions to complex engineering decisions involve complementary intelligence capabilities (Kiral, 2025).

The cognitive architecture of the framework is fairly successful in making the connection between bottom-up, data-driven AI and top-down, knowledge-based engineering practice. This combination of deep learning for pattern recognition in large data sets and fuzzy logic and knowledge-based components for interpretability and regulatory insight is crucial for engineering applications (Sanchez et al., 2024). Multi-agent architecture allows decisions to be made for multi-stakeholder, multi-objective situations typical with infrastructure projects.

A practically significant improvement with an accuracy of 34.7% in decision making has been achieved, which could result in significant economic and safety impacts in infrastructure delivery. Addressing a critical bottleneck in project delivery, the 56.2% decision time reduction helps to eliminate delays and cost overruns caused by extended decision periods (Ujjwal & Chodorowski, 2019). But in practice the value of the framework is highly reliant on the quality and comprehensiveness of the data it accesses, creating a constraint in situations where there is poor information management. The explainability results are particularly significant for engineering practice. Unlike black-box deep learning models, the provides traceable reasoning chains that combine quantitative analysis with qualitative judgment, enabling engineers to understand, verify, and potentially override AI recommendations . This human-AI collaboration model aligns with professional engineering ethics and liability frameworks.

Comparison with existing literature confirms the novelty of the integrated approach. While individual components (BIM, deep learning, fuzzy logic, multi-agent systems) have been applied separately in construction research , the cognitive integration demonstrated in CAC-BIM represents a qualitative advancement in capability. The framework's performance exceeds reported results from single-technique approaches by margins of 15-25% across comparable evaluation metrics .

## 5. Conclusion and Future Work

This research has designed and validated a Computer Aided Cognitive BIM framework based on hybrid artificial intelligence techniques for intelligent decision making on civil engineering infrastructure. Second, the multi-layered CAC-BIM architecture is able to integrate BIM information environments and cognitive AI processing in one platform, which effectively supports infrastructure decision-making. This five-layer architecture (Data Acquisition, Knowledge Representation, Cognitive Processing, Decision Synthesis and Interaction) offers a broad approach that embraces all the aspects of the decision-making process in civil engineering projects. Second, the hybrid AI approach with the integration of deep learning, fuzzy logic, multi-agent systems, and knowledge-based reasoning shows synergistic performance improvement of 12.4% from the best individual component and 34.7% from the conventional BIM-assisted approach. This confirms the theoretical idea that there is need for complementary AI capabilities for different aspects of the decision problem in the case of complex infrastructure decisions. Third, the framework yields practical performance levels for engineering deployment, decision accuracy of more than 89%, regulatory compliance of 100%, and decision time savings of more than 56%. The expert evaluators have given the explainability capabilities a score of 4.3/5.0, highlighting the importance of the ability in safety-critical engineering applications. Fourth, the multi-agent negotiation mechanism successfully copes with conflicting objectives of the stakeholders and multi-criteria optimization, providing balanced solutions that satisfy structural safety, economic efficiency, environmental protection and regulation, at the same time. The BDI agent architecture delivers principled reasoning in a way that is similar to the professional engineering judgement processes. Fifth, the Case Based Reasoning component can provide valuable contextual intelligence by searching for relevant precedents in historical project databases, thus enhancing current decisions with experiential knowledge. This ability provides a solution to this problem as the construction industry faces the issue of retaining knowledge that is often lost when experienced engineers retire.

## *5.1 Contributions to Knowledge*

The significant value added to the knowledge base of civil engineering informatics and AI is the CAC-BIM framework itself, which is the first integrated cognitive architecture developed specifically for BIM-based support for infrastructure decision making through hybrid AI. The framework offers a flexible architecture template that can be customized for other kinds of infrastructure and decision situations. The second contribution is a hybrid knowledge representation scheme, a blend of ontological and neural representations and case libraries, in a single BIM-centric information space. This scheme allows deductive, inductive and analogical reasoning at the same time, thus offering a fuller cognitive capability than any of the single representation schemes. The tertiary contribution is the empirical evidence of the generalizability of the framework in different infrastructure types, project scales and decision contexts through three diverse infrastructure case studies. Comparative data gives a guide to the performance in the future research in this area. The fourth is the first one that demonstrates how explainable AI can be realized in complex engineering decision support using hybrid architectures that incorporate data-driven and knowledge-based reasoning. This is an important challenge to overcome in the application of AI in professional engineering practice.

## *5.2 Practical Implications*

The CAC-BIM has practical implications in the field of Civil Engineering. For design organizations, the framework offers intelligent decision support to complement engineering skills, minimise design cycles and maximise resource usage. The framework is used for construction planning, risk management and real-time decision making during construction projects by construction companies. The framework provides asset owners and operators a way to optimize asset life cycles for predictive maintenance planning, rehabilitation optimization, and lifecycle cost management.

It is modular, facilitating the implementation in stages to allow organizations to implement certain modules as needed and progressively enable full cognitive BIM. Being cloud-based, it can scale easily and be accessed without the need for a large local computing setup. An IFC interface with common BIM software (Revit, Tekla, Civil 3D) means that the software is compatible with your existing workflow and that there is a minimal impact on your organization.

## *5.3 Limitations*

While this is all positive, there are a number of drawbacks to be noted. The case study validation is detailed but only covers three projects, and may not necessarily encompass the range of infrastructure decision contexts worldwide. Its performance relies on the quality and completeness of data, and the performance may be compromised if the organization has inferior information management practices. Real-time processing of large-scale infrastructure models is still quite a bit compute-intensive, which may make it difficult to deploy in resource-constrained environments. There is a cost of maintenance to the knowledge base to keep up with changes in codes, standards and best practice, as well as to keep the knowledge base current. The expert evaluation panel was diverse, however there were a maximum of 12 members present and may not reflect the industry voice as a whole. The framework is primarily concerned with the technical dimension of decision making and has limited scope of political, social and organizational aspects of infrastructure decision making. The natural language interaction features are useful but have not been tested for multilingual use, so may not be immediately useable in other language areas.

## *5.4 Recommendations for future research.*

Given the results and limitations found, there are some directions that may be suggested for future research: The first one is to extend the framework to include the digital twin functionalities and real-time synchronize between physical infrastructure and cognitive BIM models. This could facilitate continuous learning and adaptive decision-making over the infrastructure lifecycle, extending from the project phase to the whole-life cognitive asset management (Yitmen et al., 2021). Second, federated learning methods can be explored to allow organizations to collaboratively train models without sharing their own project data. This would remove the limitation of data scarcity without compromising commercial confidentiality, and allow for the benefits of wider industry experience to be taken. Third, integration of Large Language Models (LLMs) to improve the natural language interaction, automated generation of reports, and interpretation of regulations should be investigated. The framework could benefit hugely from domain-specific language models that will be optimized for non-technical stakeholders. Fourth, the framework should be expanded to include aspects of sustainability and climate resilience decision making, including lifecycle carbon assessment, climate projection information and principles of circular economy in the cognitive reasoning process. This is in line with the international agendas for sustainable infrastructure. Fifth, there is a need for longitudinal studies on the deployment of frameworks across multiple project cycles to generate evidence on long-term performance, learning effects, and ROI. These studies would provide more body of evidence for industry uptake and inform framework evolution.

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