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A CONCEPTUAL FRAMEWORK FOR AUTOMATING CONSTRUCTABILITY ANALYSIS IN CONSTRUCTION PROJECTS

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ABSTRACT: The complexity and scale of modern construction projects increasingly demand efficient constructability analysis to optimize design, safety, and overall project performance. Traditional constructability analysis, often reliant on manual review and expertise, faces limitations in consistency and scalability, particularly as project data becomes more extensive and diverse. This paper proposes a novel conceptual framework for automating constructability analysis, integrating data processing, machine learning, and rule-based algorithms to streamline constructability analysis. The framework incorporates multiple layers, including input data and knowledge base integration and machine learning models. This structure enables continuous learning and iterative improvements, providing timely feedback to the design phase, which in turn facilitates more informed decision-making. By automating the constructability analysis process, the proposed framework aims to reduce design errors, enhance project planning, and support constraint optimization. Additionally, the framework's scalability positions it as a valuable tool across various project types and sizes, broadening the application of automated constructability practices in the construction industry. This paper outlines the framework’s conceptual design and suggests an evaluation approach to eventually compare the automated system’s outputs with traditional constructability assessments, through expert validation, highlighting its potential to enhance construction project outcomes through efficient, data-driven automation.

1. INTRODUCTION

1.1 Background

The construction sector continues to encounter significant obstacles, including persistent cost escalations, schedule deviations, suboptimal resource allocation, and misalignment between design and construction phases. These challenges are often attributed to insufficient integration of multidisciplinary knowledge and inadequate stakeholder coordination during the early stages of project development (O’Connor and Miller 1994). Furthermore, unforeseen geotechnical conditions, workforce constraints, and logistical complexities exacerbate execution risks. With the rising emphasis on sustainable construction practices and environmental stewardship, these systemic inefficiencies highlight the critical need for methodological advancements to enhance project delivery frameworks (Smith and Wong 2022). Constructability analysis has emerged as a robust methodology to address these multifaceted issues by embedding construction-centric knowledge into the early stages of project planning and design. Through comprehensive evaluations of design schematics and rigorous analysis of site-specific conditions, constructability analysis proactively identifies potential impediments, enabling stakeholders to implement pre-emptive corrective strategies. This integrative approach enhances decision-making, mitigates project risks, and ensures technical feasibility while minimizing cost and schedule overruns. Furthermore, constructability analysis fosters a dynamic feedback loop, wherein iterative insights from construction teams are systematically integrated into design refinements, improving overall project coherence and practicality (Faraji et al. 2023; Moradi and Sormunen 2023).

Furthermore, the challenges in traditional constructability analysis are exacerbated by the increasing complexity of modern industrial projects. As industrial designs grow more sophisticated, they require more nuanced analyses to account for numerous interdependent factors, including material selection, construction methods, sequencing, logistics, and safety considerations. These factors must be evaluated alongside cost and schedule constraints, further increasing the demand for efficient and accurate constructability assessments. Despite the critical importance of this process, the construction industry has yet to fully capitalize on advancements in automation through AI, particularly machine learning, to streamline and enhance constructability analysis. Despite its benefits, the practical implementation of constructability analysis often faces limitations, such as the dependency on experienced professionals, the time-intensive nature of manual reviews, and the lack of standardized methodologies across projects. These constraints highlight the need for automation in constructability analysis to ensure consistency, efficiency, and scalability across diverse construction projects. Automation leverages advanced computational tools to reduce reliance on manual processes and enhance the precision of constructability assessments. For instance, technologies such as Building Information Modeling (BIM) and artificial intelligence (AI) enable high-fidelity simulations of construction processes, predictive analytics for risk assessment, and automated optimization of material and labor resources. These tools not only streamline workflows but also integrate sustainability objectives by optimizing material efficiency and minimizing environmental impacts (Gan et al., 2025).

However, the automation of constructability analysis is not without its challenges. The implementation of AI and BIM technologies often requires significant upfront investment, advanced technical expertise, and seamless integration with existing project management systems. Additionally, automated systems may struggle to replicate the nuanced judgment and tacit knowledge provided by experienced professionals, potentially leading to oversights in complex projects. Data quality and interoperability also pose significant barriers, as fragmented or incomplete data can undermine the accuracy and reliability of automated constructability assessments (Ding et al. 2020; Kifokeris and Xenidis 2017). Several studies have examined the evolution, methodologies, and applications of constructability analysis across various project types. Early reviews primarily explored the integration of constructability concepts during the design and planning stages, emphasizing their role in reducing project risks and enhancing efficiency. For instance, a study by Pettee (2012) discussed the importance of constructability reviews in identifying potential issues early in the project lifecycle to mitigate risks and improve project outcomes. Other studies have examined the development of structured approaches, such as checklists and guidelines, to systematically incorporate construction knowledge into design processes. For example, research by Girardet (2021) highlighted the use of constructability concepts to enhance project performance through systematic reviews and the application of best practices. Zhang et al (2022) discussed how combining BIM and AI can lead to smarter construction management by enabling more efficient data handling and decision-making processes. Whilst the existing reviews mainly focus on the adoption of constructability analysis during the early stages of design, there is lack a comprehensive coverage of advanced technologies and their specific applications in automating the constructability analysis process, leaving a critical gap in the literature.

BIM technologies do not only serve as the primary repository of structured project data but can also facilitate efficient communication and collaboration among multidisciplinary stakeholders throughout the project lifecycle, which can be complemented with advanced computational techniques, such as machine learning (Zhang et al., 2022). Machine learning (ML) offers powerful predictive analytics by identifying patterns within historical project data, thereby helping to foresee scheduling conflicts, resource bottlenecks, amongst other risks (Uddin et al., 2024). ML technologies such as Large Language Models (LLMs) and Graph Neural Networks (GNNs) can be promising in streamlining constructability analysis within BIM environments by extracting meaningful insights from unstructured project documentation (He et al., 2024) and identifying complex relational anomalies within the digital model (Jia et al., 2023). LLMs are designed to process and generate human-like text and extract semantic meaning from unstructured textual data. In construction projects, a vast amount of unstructured information, such as contracts, specifications, design documents, and progress reports, is generated and stored alongside the structured BIM data. Goa et al (2024) utilized LLMs, to analyze and extract key features from textual project data, detect patterns, and derive context by automatically summarizing lengthy project documents, interpreting ambiguous instructions, and generating insights or recommendations based on historical data. On the other hand, GNNs represent a specialized class of ML models tailored to process graph-based data structures, mirroring the interconnected nature of BIM environments. GNNs excel at modeling the complex relationships among project components, thereby effectively identifying anomalies like clashes or overlapping elements that may not be readily visible in traditional analysis (Jia et al., 2023). Integrating BIM with these LLMs and GNNs creates a synergistic framework that could significantly improve the accuracy and efficiency of constructability assessments, where BIM delivers the structured data environment, while LLMs extract and analyze both quantitative and qualitative project data, and GNNs detect complex relational anomalies, which will not only address the limitations of manual evaluations, but also position the system to provide clearer and more accurate insights which is critical for proactive and better informed decision-making in construction projects.

This research seeks to address this deficiency by automating constructability analysis through the integration of BIM and machine learning techniques. The study is grounded in three core objectives that aim to establish a robust framework for automating constructability analysis. The anticipated outcomes of this study include more accurate, efficient, and standardized constructability assessments, leading to better-informed decision-making and reduced project risks. By transitioning from traditional to automated methods, this research aspires to empower stakeholders with tools that streamline the constructability analysis process, align designs more closely with construction realities, and improve overall project performance. In doing so, it will contribute to the advancement of knowledge in both constructability analysis and the broader application of artificial intelligence and machine learning in construction engineering.

1.2 Problem Statement

Constructability analysis is a critical component of successful project delivery, particularly for industrial projects, which are often characterized by high complexity, specialized requirements, and stringent safety standards. When conducted exclusively during the pre-construction phase, this analysis plays a crucial role in identifying potential challenges and optimizing plans before the project moves to execution. The focus during this stage is on leveraging available design and planning data to assess feasibility, improve resource allocation, and mitigate risks. However, the early-stage nature of pre-construction analysis demands robust frameworks, collaborative efforts, and advanced predictive tools to address the unique complexities of projects effectively. Despite its importance, the construction industry continues to face significant challenges in implementing effective constructability analysis. The practical challenges faced by the industry include 1) limited access to comprehensive and high-quality project data, such as detailed designs, specifications, and past project records, makes it difficult to perform accurate constructability analysis, 2) limited early collaboration between stakeholders where the lack of effective integration between designers, engineers, and construction teams during the early stages often results in decisions that do not adequately consider construction feasibility, 3) difficulty in predicting construction constraints due to the lack of in-time feedback from the construction phase, where predicting potential constraints such as site logistics, sequencing issues, or equipment accessibility becomes a challenge, leading to oversights during planning, and the 4) reliance on static and generalized tools since many constructability analysis methods used prior to the start of construction rely on static models or generalized tools that cannot fully capture project-specific complexities or adapt to dynamic project requirements.

1.3 Research Objectives

To address the identified industry challenges and research gaps, the following research aims to address a number of research objectives to propose and develop an innovative data-driven predictive tool to enhance and automate constructability analysis for industrial projects. The objectives are to: 1) identify and analyze constructability factors that can be quantified and modeled using advanced technologies with particular emphasis on their relevance to industrial projects 2) enhance data collection and preprocessing methods to leverage project data, such as drawings, schedules, and specifications, ensuring the accuracy and completeness of inputs by creating a standardized and centralized data collection and management framework that integrates design details, material specifications, site conditions, and other critical information, ensuring consistent and comprehensive inputs for constructability analysis, and to 3) develop a dynamic and adaptable predictive modeling tool capable of predicting potential construction constraints, using historical data and advanced technologies tailored to anticipate possible issues that could arise related to site logistics, sequencing conflicts and equipment accessibility, and evaluate constructability challenges prior to execution.

2. PROPOSED FRAMEWORK RESEARCH METHOD

This section outlines a proposed development process of the conceptual framework. The research method is divided into six distinct stages, where each stage builds upon the previous, methodically addressing various facets of the research aim to integrate machine learning techniques and a domain-specific ontology to enhance constructability analysis in industrial projects. The methodology is designed to ensure a comprehensive approach to developing, testing, and validating the tools and processes necessary for effective data integration and analysis. Starting with the initial scoping and identification of challenges faced by the industry, the framework progresses through the development and integration of a tailored ontology, the implementation of advanced machine learning technologies for anomaly detection and ends with the deployment of a user interface that supports user interaction and predictive analytics. This systematic progression ensures that each component is robustly developed and integrated into the framework, providing a foundation for model implementation with real-world projects.

2.1 Data Collection and Analysis

In the initial stage of our research, we focus on delineating the project's scope and identifying key constructability factors that are flexible to quantification and modeling using machine learning techniques. This foundational phase is critical as it sets the stage for a structured approach to capturing and utilizing historical data effectively. The first activity of this stage involves a thorough identification of the problem definition and identifying the constructability factors crucial for evaluating and analyzing industrial projects. This step ensures that the research is precisely targeted and grounded in real-world constructability challenges. Subsequently, we engage with industry experts through interviews to validate and refine these factors. This interaction helps in identifying the most critical elements that should be included in the ontology, ensuring that it reflects both theoretical and practical considerations of constructability. The third activity focuses on the systematic collection of historical data from various projects. This includes the aggregation of Building Information Modeling (BIM) models, project drawings, and documentation such as specifications, contract conditions, and requests for proposals and information. Additionally, records of previously encountered issues are also collected. This methodical collection and analysis of data are integral for achieving a deep and nuanced understanding necessary for the subsequent development of an ontology and for the effective training of the machine learning models. This stage directly addresses Objective 1 of the research, setting the foundation for model development in later stages. Each of these activities is interlinked, creating a coherent methodology that leverages both expert insight and empirical data to tackle the challenges of constructability in industrial projects.

2.2 Design and Development of Ontology

In Stage 2 of our research, we aim to develop an ontology that systematically categorizes and relates key concepts, classes, attributes, and relationships essential for integration within a BIM environment. This ontology will serve as a structured framework to facilitate consistent data handling, feature extraction, and semantic analysis, thus partially addressing Objective 2 of our research. The development of this ontology is structured into three main activities. First, we identify the critical attributes for each class and establish the relationships between these classes. This activity leads to the creation of a hierarchical structure that illustrates the interconnections among different classes and concepts. Next, we proceed to convert these identified concepts, attributes, and relationships into a formal ontology schema using an appropriate ontology representation language. This schema acts as a blueprint for the ontology, structuring information in a way that is both computationally efficient and meaningful for BIM applications. The final activity involves the validation and refinement of the ontology. We apply the initial ontology to sample datasets to test its functionality and identify any inconsistencies or gaps. By comparing the structure of the ontology with real-world data, we can pinpoint areas that require adjustment. This ontology is then refined based on feedback from industry experts and validation results, ensuring its reliability and applicability in real-world settings. Each of these activities is interconnected, ensuring a thorough approach to developing an ontology that is both robust and aligned with the needs of the BIM environment.

2.3 Semantic Feature Extraction Module

In the following third stage, we employ advanced language models to extract semantic features from textual data, a process crucial for understanding the context and relationships within the data. This capability is important for training the machine learning models and enhancing data analysis, thereby partially addressing Objective 2 of our project. This stage is divided into four research activities, ensuring a structured and comprehensive approach. Initially, we engage in Language Model Selection, where various language models are tested and analyzed to select the one that best fits the complexity and scale of our data. This selection process is an important step to ensure that the subsequent semantic feature extraction is accurate and efficient. Following model selection, we align the data and ontology schema developed in stage 2 with a semantic feature extraction module. This integration utilizes LLM technology to extract and analyze semantic features from the aggregated data, enabling deeper and more nuanced data interpretation. The next activity involves configuring the module to recognize and categorize data accurately according to the ontology schema. This configuration includes programming the extraction tools to map extracted features directly to corresponding elements in the ontology and manually annotating a subset of the data to serve as training data. This preparation allows the extraction module to operate effectively within the defined schema. Finally, validation of the extracted features is conducted. Initial results from the semantic feature extraction would then be used to test and refine the ontology, which is an important step to verify that the features are being correctly identified and categorized.

2.4 BIM and Ontology System Integration

Stage 4 works on integrating the ontology developed in Stage 3 with a BIM system, as is shown in Figure 1. This integration is aimed at enhancing the functionality of BIM systems and enabling more sophisticated data analysis and management capabilities. By merging the semantic and structured data from the ontology with BIM systems, we would facilitate a seamless flow of information across projects of similar scope, all within a single integrated system. This effort directly addresses research Objective 2, leveraging the developed ontology to maximize the utility and efficiency of BIM environments. The integration process is organized into two distinct research activities. The first activity, Selection of Integration Technologies, involves a thorough assessment of the available tools and technologies that can facilitate the integration of the ontology with BIM systems. This includes evaluating various Application Programming Interfaces (APIs) and other middleware solutions that can bridge the gap between the ontology's semantic structure and the data handling capabilities of BIM systems. The second activity, Implementing Data Mapping, is focused on developing a schema that effectively maps the classes and attributes of the ontology to corresponding elements within the BIM system. This mapping is essential for ensuring that data flows seamlessly between the ontology and the BIM system, maintaining data coherence. The development of this schema involves a detailed analysis of both the ontology structure and the BIM system’s data architecture to ensure comprehensive coverage and functionality. Together, these activities ensure that the ontology's rich semantic framework is fully utilized within BIM systems, enhancing their analytical and management capabilities and contributing significantly to the field of construction management.

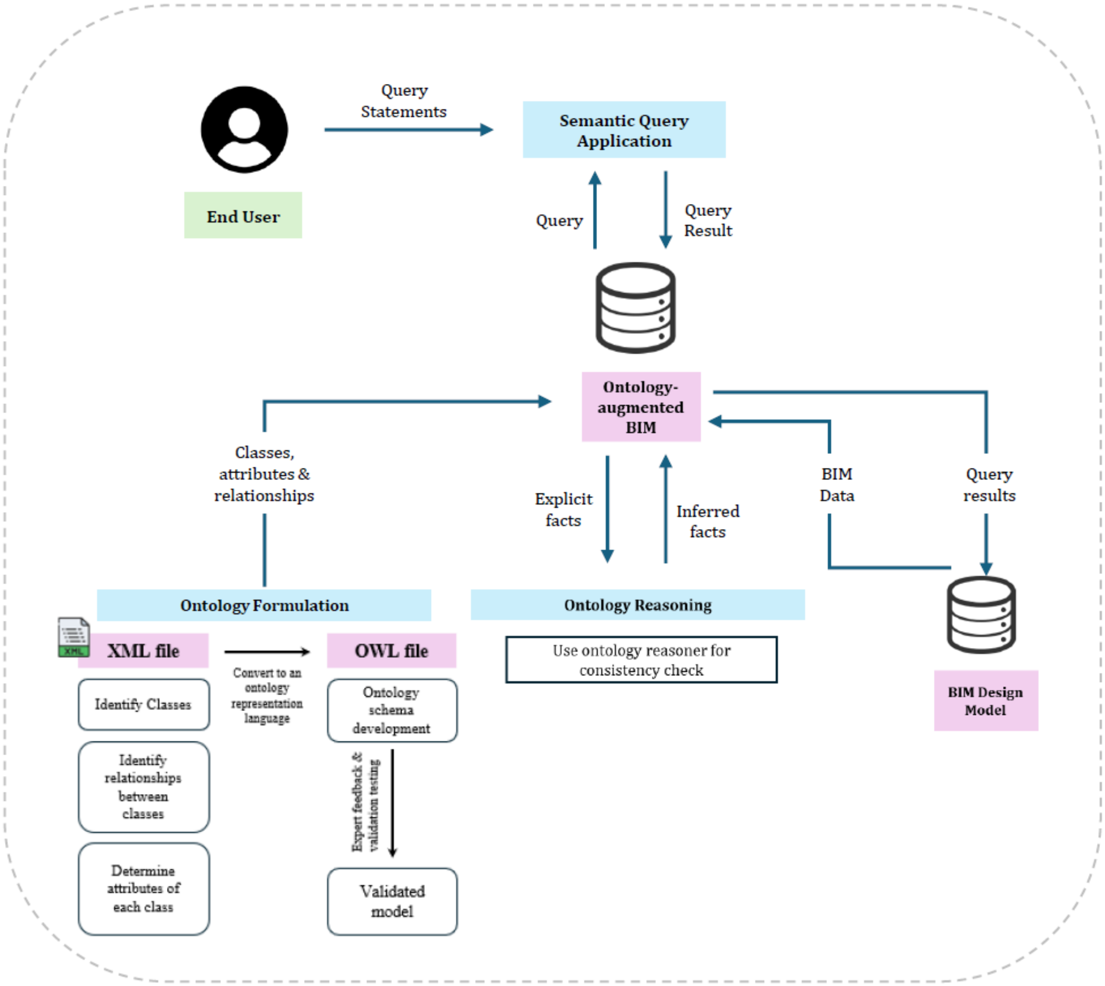

Figure 1: Integrated Ontology-BIM System Methodology

2.5 Prediction Model Development

Stage 5 concentrates on the development and implementation of a machine learning model, specifically utilizing Graph Neural Network (GNN) techniques, to detect anomalies in BIM systems. This stage leverages the dataset created through the integration of the ontology with the BIM system, as established in Stage 4, aiming to enhance predictive analytics within BIM environments. By employing structured data for machine learning, this stage seeks to advance anomaly detection, hence automating the constructability analysis process. This effort partially addresses Objective 3, focusing on applying advanced data analysis techniques in practical settings. The development of this machine learning model is divided into four key research activities. Initially, it involves the creation of a GNN-based model that can identify different types of anomalies, such as clashes and overlapping elements within the BIM system, utilizing the integrated ontology-BIM data structure. Subsequently, the model is trained on a dataset that includes manually annotated and tagged instances of previously identified anomalies and conflicts. This training process is essential for tuning the model to recognize and differentiate between normal operations and potential issues accurately. Following training, the model's performance is accessed using a separate testing dataset. This evaluation is needed to verify that the model can reliably identify anomalies, and also for making any necessary adjustments to improve its accuracy and effectiveness. Finally, the trained model is integrated with the existing Ontology-BIM system, to allow for the operation of the machine learning model within the BIM environment, enabling it to interact with other system components and contribute to anomaly detection and management. Through these activities, Stage 5 aims to harness the power of machine learning to bring about significant improvements in the management and operational oversight of construction projects using

BIM systems. This stage not only enhances the predictive capabilities within BIM environments but also sets a foundation for further innovations in construction project analytics.

2.6 User Interface Implementation and Deployment

In the final stage, we focus on deploying an interactive user interface that enables stakeholders to input new project data, receive anomaly prediction alerts. This stage translates the machine learning capabilities developed in earlier stages into a practical, user-centered application that enhances decision-making and project management within BIM environments. This user interface would not only integrate with the other developed systems but would also to support dynamic interactions with the user through semantic queries using natural language processing technologies. This stage initially starts with the development of a sophisticated user interface that allows users to easily input new project data into the system. The interface would facilitate the smooth uploading of data, which is then processed by the underlying machine learning models for anomaly detection. As new data is inputted, the LLM and GNN models would analyze it to predict anomalies. Upon detecting any discrepancies, the system automatically generates alerts. These alerts are tailored to the severity and specifics of the anomaly, ensuring that users receive timely and relevant notifications. A key feature of this stage is the integration of an LLM that allows users to make semantic queries about the data or the operational status of the project. Users can ask questions in natural language, and the system provides responses based on the data analyzed by the model. This feature makes the system interactive and greatly aids in decision-making.

Lastly, the entire system would then undergo rigorous testing and validation to ensure its accuracy and usability. This includes testing the user interface for user experience quality, the anomaly prediction for accuracy, and the alert system for responsiveness. Feedback from these tests is used to refine the system iteratively, enhancing its functionality and user-friendliness. By the end of this stage, the system will not only support proactive management through predictive analytics but will also equip users with a robust tool for continuous interaction and query-driven exploration of project data.

3. DISCUSSION

This research posits that the integration of machine learning techniques, large language models, and a domain-specific ontology can significantly enhance the accuracy and efficiency of constructability analysis in industrial projects. The proposed ontology will serve as a structured framework to combine and organize disparate project data, ranging from textual descriptions in project documentation to quantitative design and scheduling parameters. This systematic data integration will allow for more effective training and application of ML algorithms and LLMs. This hypothesis is based on the premise that machine learning can uncover patterns and correlations in complex project data that are not immediately apparent to human analysts, while LLMs can interpret and process the vast amounts of unstructured textual data contained in project reports, contracts, and planning documents. Together, these technologies could provide a more nuanced understanding of project complexities, enabling predictive analytics that foresee constructability challenges based on historical data and current project inputs. The aim of this approach is to reduce project delays and cost overruns by facilitating more informed planning and decision-making processes. The feasibility and effectiveness of this integrated approach will need to be evaluated through a series of tests where neural networks and LLMs will be trained on the ontology-organized dataset, aiming to validate the models' predictive accuracy and practical utility in real-world scenarios.

A comprehensive system architecture for automating constructability analysis in construction projects was designed by integrating insights from a detailed literature review and practical engagement with industry professionals. Initially, a comprehensive literature review was conducted to identify the existing gaps related automating constructability analysis and to understand the current methodologies used in the industry. This was complemented by direct engagements with industry professionals which provided valuable insights in framing the research problem. Combining inputs from both research and industry sources led to the design of a system architecture that would address both theoretical and practical needs, as is shown in Figure 1.

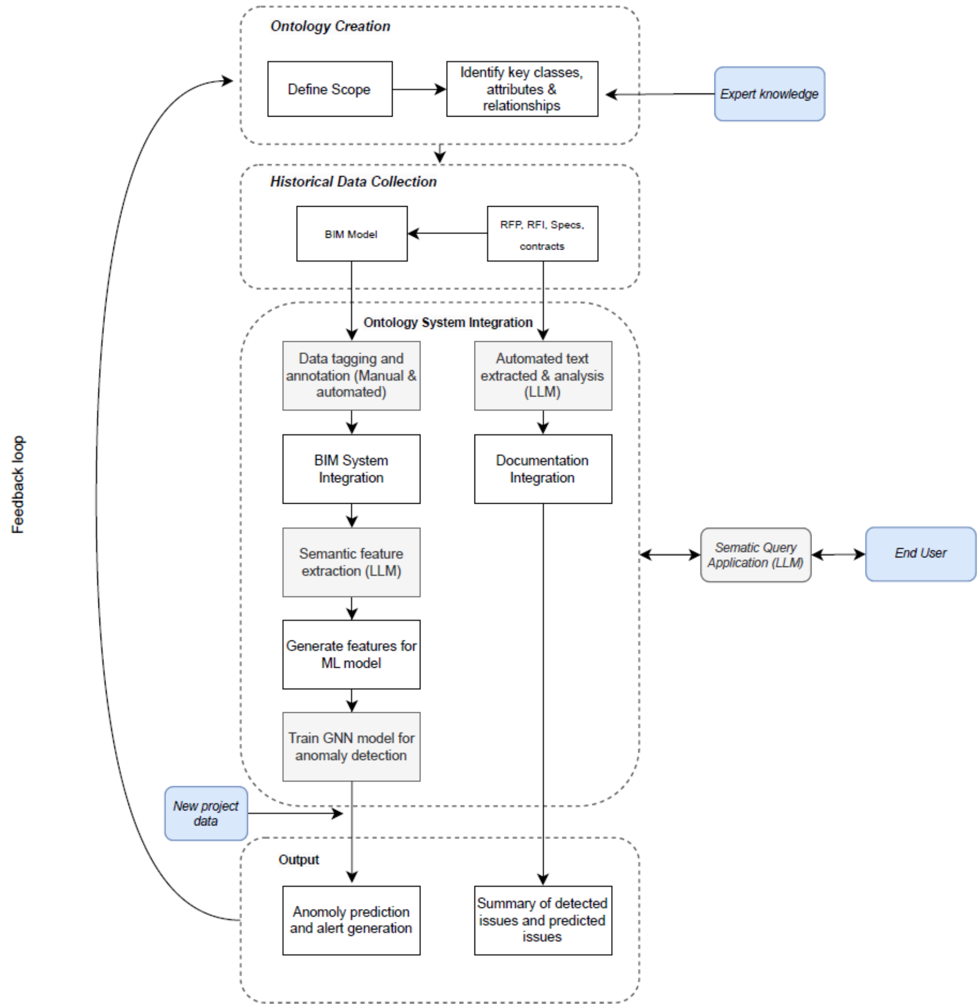

Figure 2: System Architecture of the Proposed Framework

This research significantly contributes to the field of constructability analysis by integrating advanced predictive analytics and interactive technologies into BIM systems. Traditionally, constructability analysis has relied heavily on manual reviews and expertise to anticipate potential construction challenges and optimize project execution plans. Our approach automates and enhances this analysis by using GNNs to detect potential constructability issues before they materialize into more significant problems. Moreover, the incorporation of a user-friendly interface and semantic querying capabilities using a LLM transforms the way stakeholders interact with BIM systems, enabling them to understand complex project data more intuitively.

3.1 Expected Contributions

There are several significant advancements that our integrated system introduces to the field of constructability analysis. Firstly, the automation of constructability analysis through our system stands out as a pivotal advancement, significantly enhancing the efficiency and accuracy of project planning and execution. By employing a GNN model for anomaly detection, our approach not only identifies potential issues early but also predicts future discrepancies, allowing for proactive adjustments that are vital in avoiding costly delays and resource misallocations. In addition, the introduction of a user-friendly interface equipped with semantic querying capabilities extends the accessibility of complex data analysis to a broader range of users, including those without deep technical expertise. This improvement in data interaction empowers project managers and stakeholders to make quick and informed decisions that are critical for the timely and budget-conscious delivery of construction projects.

Academically, this study enriches the literature on the application of machine learning in construction management, presenting a novel methodology for integrating predictive analytics into BIM systems. Practically, the research outputs a tangible tool that significantly advances traditional constructability analysis, offering a more dynamic and responsive approach to managing construction projects. The flexibility and adaptability of our system ensure that it can be tailored to various project needs and complexities, making it a versatile and invaluable tool in diverse construction environments. This contribution is not merely theoretical but has practical implications that aim to transform traditional construction management practices.

3.2 Limitations and Future Work

While this study proposes a novel conceptual framework for automating constructability analysis using machine learning, ontology modeling, and BIM integration, it remains at the conceptual stage and has not yet been validated through implementation in real-world projects. The integration of advanced computational techniques such as LLMs ang GNNs with BIM workflows faces significant practical challenges. In particular, implementing this system in real-world settings would require addressing complex issues such as data preparation, ensuring high-quality datasets for model training, and achieving seamless interoperability among diverse technologies. To mitigate these challenges, our framework has been intentionally designed in a modular fashion, allowing individual components to be developed, tested, and refined independently. For instance, the semantic feature extraction module using LLMs, and the anomaly detection module using GNNs, can each be validated using simulated datasets or case studies prior to full-scale deployment. This modular approach enables phased validation, lowering the barrier to early-stage experimentation and facilitating gradual integration into current industry workflows.

In addition, we acknowledge that widespread implementation in the construction industry presents challenges. These include the need for structured and unstructured data collection, training of machine learning models, and the integration of ontology-driven systems into existing BIM platforms. However, such challenges are not insurmountable. We are actively collaborating with industry partners through every step of the research method for the integration of expert knowledge within the research stages, and to conduct pilot studies on real-world construction projects. These partnerships will also enable access to project documentation, BIM models, and performance feedback data, which are essential for training and testing the framework's components. Accordingly, while the full realization of the proposed framework involves substantial integration and technological maturity, we believe the incremental implementation and validation of its core components can provide significant value, allowing the industry to transition toward more data-driven and automated review systems.

4. CONCLUSION

In conclusion, this research proposes a conceptual framework that integrates machine learning techniques, large language models, and a domain-specific ontology to enhance constructability analysis in industrial projects. While this framework has not yet been applied, its potential to automate the constructability analysis presents a novel approach. By automating the identification and prediction of potential issues within BIM systems, the framework aims to pre-emptively address challenges that could lead to costly delays and resource misallocations. The proposed integration of a user-friendly interface equipped with semantic querying capabilities offers a transformative approach to interacting with complex project data. This feature is designed to make advanced data analytics accessible to a broader range of users. Furthermore, the framework's predictive capabilities, developed through the application of GNN models, enhances the accuracy of anomaly detection, hence adding an early warning system in place prior to the commencement of construction. This conceptual framework lays the groundwork for a tool that could significantly streamline construction project management, offering a more dynamic and responsive approach to handling construction challenges. Future research should focus on validating this framework through empirical studies and real-world projects to refine its components and verify its effectiveness in real-world settings. Despite its promising potential, the implementation of this framework faces several challenges and limitations. Future research should focus on addressing these potential hurdles, such as the high initial costs and complexity of integrating AI and BIM technologies into existing project management systems. There may also be resistance to adopting new technologies from stakeholders accustomed to traditional methods. Additionally, the reliability and effectiveness of the machine learning models depend heavily on the quality and comprehensiveness of the data used, which can be limited by issues of data interoperability and fragmentation across different construction project platforms. Furthermore, the nuanced judgment and tacit knowledge provided by experienced professionals are difficult to fully replicate with automated systems, which could lead to oversights in complex scenarios. These areas present several avenues for testing and refining the framework to verify its effectiveness in the practical world.

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