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AI-BASED FINANCIAL RISK AND COST PREDICTION FRAMEWORK FOR CONSTRUCTION EXPERIMENTS: A CASE STUDY OF STEEL HALL ASSEMBLY

Summary: This study proposes an artificial intelligence-based framework for financial risk assessment and cost prediction in construction experiments, focusing on steel hall assembly processes. Construction experiments involving real-time monitoring technologies are associated with significant financial uncertainty. Proposed framework combines cost modeling, risk classification and data-driven prediction using a multilayer perceptron (MLP) model. Input variables include the number of structural elements, assembly duration, labor engagement, detected errors and safety-related events. The model predicts costs and associated risk levels, which are compared with actual outcomes from a controlled steel hall assembly experiment. The case study demonstrates the framework's applicability in identifying cost deviations and financial risk patterns. Results indicate that the approach enables early detection of potential cost overruns and improves decision-making in the planning and execution of construction experiments. Integrating artificial intelligence with financial analysis can improve resource management and provide a basis for applying the framework to a broader range of construction scenarios.

Keywords: artificial intelligence, cost prediction, financial risk, construction experiments, steel hall assembly, MLP model

PROCENA FINANSIJSKOG RIZIKA I PREDVIĐANJE TROŠKOVA U GRAĐEVINSKIM EKSPERIMENTIMA POMOĆU VEŠTAČKE INTELIGENCIJE: STUDIJA SLUČAJA MONTAŽE ČELIČNE HALE

Rezime: Ova studija predlaže okvir zasnovan na veštačkoj inteligenciji za procenu finansijskog rizika i predviđanje troškova u građevinskim eksperimentima, sa fokusom na montažu čeličnih hala. Građevinski eksperimenti sa praćenjem u realnom vremenu donose značajnu finansijsku neizvesnost. Predloženi okvir kombinuje modelovanje troškova, klasifikaciju rizika i predviđanje zasnovano na podacima pomoću modela višeslojnog perceptrona (MLP). Ulazne promenljive obuhvataju broj konstruktivnih elemenata, trajanje montaže, angažovanje radne snage, uočene greške i bezbednosne događaje. Model predviđa troškove i nivoe rizika koji se porede sa stvarnim ishodima kontrolisanog eksperimenta montaže čelične hale. Rezultati pokazuju da pristup omogućava rano otkrivanje potencijalnog prekoračenja troškova i poboljšava donošenje odluka. Integracija veštačke inteligencije i finansijske analize doprinosi transparentnijem i efikasnijem upravljanju resursima i pruža osnovu za primenu okvira u različitim građevinskim scenarijima.

Ključne reči: veštačka inteligencija, predviđanje troškova, finansijski rizik, eksperimenti u građevinarstvu, montaža čeličnih hala, MLP model

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1. INTRODUCTION

Total Construction projects are inherently associated with financial uncertainty, particularly in experimental environments where innovative technologies and non-standardized processes are applied. Unlike conventional construction activities, experimental setups—such as monitored assembly of structural systems—introduce additional layers of complexity, including variability in execution time, equipment performance, labor productivity, and safety conditions. These factors often lead to deviations between planned and actual costs, creating challenges for effective financial planning and risk management.

In recent years, artificial intelligence (AI) has emerged as a powerful tool in construction management, enabling improved prediction, monitoring, and decision-making across various domains (Golparvar-Fard et al., 2015; Bock & Linner, 2016). Applications of AI have primarily focused on safety risk detection, schedule optimization, and productivity analysis. However, the integration of AI techniques into financial analysis—particularly in the context of construction experiments—remains limited. Existing cost estimation methods are typically based on deterministic or statistical approaches that do not fully capture the dynamic and uncertain nature of experimental construction processes.

Financial risk in construction is traditionally evaluated using historical data and predefined cost models, which are often insufficient when applied to experimental scenarios characterized by incomplete data and evolving conditions. In such contexts, the ability to predict cost deviations and assess risk levels in real time becomes crucial. The lack of integrated frameworks that combine financial modeling, risk assessment, and AI-based prediction represents a significant research gap (Lu et al., 2020).

This study addresses this gap by proposing a comprehensive framework for financial risk assessment and cost prediction in construction testing environments using artificial intelligence. The framework is designed to integrate multiple sources of information, including operational parameters, performance indicators, and event-based data collected during the assembly process. A multilayer perceptron (MLP) model is employed to analyze the relationships between input variables and financial outcomes, enabling data-driven prediction of costs and associated risk levels.

The proposed approach is validated through a case study involving the assembly of a steel hall, where experimental monitoring techniques are applied to track construction activities (Cheng & Teizer, 2013). The study compares predicted costs with actual financial outcomes, providing insight into the accuracy and applicability of the developed model. In addition, the framework supports the identification of key factors influencing cost variability, contributing to improved financial planning and decision-making.

The main contributions of this research are threefold. First, it introduces an AI-based framework that integrates financial risk analysis with monitoring of experimental construction settings. Second, it demonstrates the practical applicability of the approach through a real-world case study. Third, it provides a foundation for further research on the use of artificial intelligence in construction finance and experimental project management.

The remainder of the paper is structured as follows. The next section presents the methodological framework, including the design of the proposed model and data processing procedures. This is followed by a literature review that situates the study within the broader context of AI applications in construction and financial risk management. The results of the case study are then presented and discussed, highlighting the performance of the proposed framework. Finally, conclusions and recommendations for future research are provided.

2. METHODOLOGY

The methodology is based on a structured framework for financial risk assessment and cost prediction in construction experiments using artificial intelligence. The methodology is designed to integrate operational, financial, and event-based data into a unified analytical model capable of predicting cost outcomes and associated risk levels. The framework is validated through a case-based experimental study involving steel hall assembly.

The methodological approach consists of five interconnected components: (1) definition of input variables, (2) data acquisition and preprocessing, (3) cost modeling, (4) artificial intelligence–based prediction, and (5) validation through comparison of predicted and actual outcomes. This structure ensures a transparent, reproducible, and scalable analytical process applicable to various construction scenarios.

2.1. FRAMEWORK OVERVIEW

The developed framework integrates construction process parameters with financial analysis and AI-based prediction. It establishes a direct relationship between operational activities and cost outcomes, enabling dynamic evaluation of financial risk during experimental execution.

The framework operates by transforming construction-related inputs into structured datasets, which are then processed through a predictive model to estimate total costs and classify risk levels. The output includes both quantitative predictions and qualitative risk indicators, supporting decision-making in planning and execution phases. The overall structure of the proposed framework is illustrated in Figure 1.

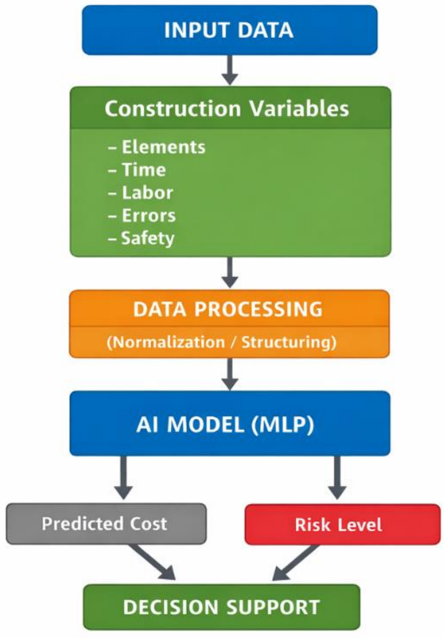

Figure 1: Proposed AI-based framework for financial risk and cost prediction in construction experiments (source: authors' research)

2.2. INPUT VARIABLES

The selection of input variables is based on the characteristics of construction experiments and factors influencing cost variability. The model incorporates the following key variables:

- Number of structural elements (columns, beams),
- Assembly duration (time required for installation),
- Labor engagement (number of workers and working hours),
- Equipment utilization (machinery involvement and operational time),
- Detected assembly errors (incorrect positioning or sequencing),
- Safety-related events (proximity risks, unsafe conditions).

These variables represent both quantitative and qualitative aspects of the construction process. Their integration enables comprehensive modeling of cost drivers and uncertainty factors.

2.3. DATA ACQUISITION AND PREPROCESSING

Data for the analysis are obtained through a combination of simulated and experimentally generated inputs within a controlled construction environment. The experimental setup includes monitoring of steel hall assembly using location-based tracking and event logging.

The collected data are standardized and transformed into a structured dataset suitable for analysis. Preprocessing includes normalization of numerical variables, categorization of event-based data, and removal of inconsistencies. This step ensures data reliability and compatibility with the predictive model.

2.4. COST MODELING

The cost model represents the financial component of the framework and is defined as a function of labor, equipment, and time-related variables. The total experimental cost is expressed as:

$$C_{total} = C_{labor} + C_{equipment} + C_{time} + C_{risk} \tag{1}$$

where:
C_{labor} represents labor-related costs,
$C_{equipment}$ denotes machinery and equipment costs,
C_{time} reflects time-dependent expenses, and
C_{risk} accounts for additional costs arising from errors and safety-related events.

This formulation allows the incorporation of both deterministic and stochastic cost components, capturing the financial impact of uncertainties inherent in construction experiments.

2.5. AI-BASED PREDICTION MODEL

A multilayer perceptron (MLP) neural network is employed to model the relationship between input variables and cost outcomes. The model is trained on the generated dataset, using normalized inputs and corresponding cost values as target outputs.

The MLP architecture consists of an input layer, one or more hidden layers with nonlinear activation functions, and an output layer producing predicted cost values. In addition to cost prediction, the model performs classification of financial risk into predefined categories (e.g., low, medium, high), based on deviation thresholds.

The training process includes data splitting into training and validation subsets, ensuring the robustness and generalization capability of the model. Performance is evaluated using standard metrics such as mean squared error (MSE) and prediction accuracy.

2.5.1. Validation and evaluation

The developed model is validated through comparison between predicted and actual costs obtained from the steel hall assembly experiment. The evaluation focuses on the accuracy of cost prediction and the reliability of risk classification.

Deviation analysis is performed to quantify the difference between predicted and observed values, providing insight into model performance. Additionally, the framework is assessed in terms of its practical applicability, particularly its ability to support financial planning and risk management in experimental construction settings.

2.6. REPRODUCIBILITY

To ensure reproducibility, the entire analytical process is structured and documented, including data preprocessing procedures, model configuration, and evaluation criteria. The framework is designed to be adaptable to different construction scenarios, allowing replication and extension in future research.

3. LITERATURE REVIEW

The application of artificial intelligence (AI) in construction engineering and management has grown significantly over the past decade, driven by the increasing complexity of projects and the need for improved decision-making under uncertainty. Machine learning (ML) and data-driven approaches have demonstrated strong capabilities in enhancing prediction accuracy, optimizing processes, and supporting risk management compared to traditional deterministic models (Bock & Linner, 2016; Mahamadu et al., 2020; Abioye et al., 2021).

3.1. AI IN CONSTRUCTION COST ESTIMATION

Cost estimation remains a critical component of construction project planning and financial management. Traditional estimation methods, typically based on historical data and expert judgment, are often insufficient in capturing nonlinear relationships among project variables (Kim et al., 2004; Sonmez, 2008).

Artificial neural networks (ANN) have been widely applied to construction cost estimation due to their ability to model complex patterns. Early studies demonstrated that ANN models can outperform conventional regression approaches in predicting project costs (Hegazy & Ayed, 1998; Kim et al., 2004). More recent research has expanded this approach using advanced ML techniques such as support vector machines (SVM), random forests, and gradient boosting algorithms (Cheng et al., 2010; Juszczyk, 2017; Wang et al., 2022).

Systematic reviews confirm that ML-based cost estimation models provide improved accuracy and adaptability, particularly in complex and data-rich environments (Mahamadu et al., 2020; Abioye et al., 2021). However, these models are typically developed using large, structured datasets from completed projects, limiting their applicability in experimental construction contexts.

3.2. AI-BASED RISK ASSESSMENT IN CONSTRUCTION

Risk assessment in construction projects has increasingly benefited from AI-based approaches, particularly in safety and operational domains. Machine learning models have been successfully used to predict accident likelihood, classify hazard levels, and support proactive safety management (Zhang et al., 2019; Tixier et al., 2016).

Recent developments include the integration of AI with digital twin technologies and real-time monitoring systems, enabling dynamic risk assessment based on continuously collected data (Boje et al., 2020; Lu et al., 2020). These approaches improve responsiveness and allow project managers to adapt to changing conditions more effectively.

Hybrid models combining statistical techniques and machine learning have also been proposed to enhance interpretability and robustness in risk prediction (Cheng & Roy, 2012; Marzouk & El-Rasas, 2014). Despite these advancements, most studies focus primarily on safety risks, while financial risk assessment remains relatively underexplored.

3.3. FINANCIAL RISK AND COST OVERRUNS

Cost overruns are a persistent issue in construction projects worldwide, often resulting from inaccurate estimation, unforeseen events, and inefficient resource management (Flyvbjerg et al., 2003; Love et al., 2013). Studies have shown that financial risks are closely linked to operational factors such as labor productivity, equipment performance, and project complexity (Doloi, 2013; Kaming et al., 1997).

Recent research has explored the use of AI for predicting cost overruns and identifying key financial risk factors. Machine learning models have demonstrated strong predictive capabilities in estimating project costs and detecting potential deviations (Cheng et al., 2010; Wang et al., 2022).

However, most of these models rely on historical project data and are not designed for experimental construction environments, where data availability is limited and conditions are continuously evolving. This limitation highlights the need for adaptive models capable of handling uncertainty and integrating real-time data.

3.4. AI IN CONSTRUCTION EXPERIMENTS AND MONITORING

The integration of advanced monitoring technologies, such as GPS, RFID, and sensor networks, has enabled the collection of high-resolution data in construction environments. These technologies support the development of intelligent systems for tracking construction activities and improving process control (Navon & Goldschmidt, 2003; Teizer et al., 2010).

Recent studies have combined monitoring systems with AI techniques to analyze construction processes, detect anomalies, and improve operational efficiency (Cheng & Teizer, 2013; Golparvar-Fard et al., 2015). Digital twin frameworks further enhance this approach by integrating physical and digital representations of construction systems, enabling real-time simulation and analysis (Boje et al., 2020).

Despite these advancements, the integration of financial analysis into monitoring frameworks remains limited. Most existing studies focus on technical and operational aspects, leaving a gap in linking monitoring data with financial outcomes.

3.5. RESEARCH GAP AND CONTRIBUTION

The reviewed literature highlights several important gaps. First, most AI-based models assume the availability of large and structured datasets, which are not typical in experimental construction environments. Second, existing approaches tend to treat cost estimation and risk assessment as separate problems, lacking integrated frameworks that combine both aspects. Third, financial analysis is often underrepresented in studies focused on construction monitoring and AI applications.

This study addresses these gaps by proposing an integrated framework that combines AI-based cost prediction, financial risk assessment, and experimental monitoring within a unified analytical model. By incorporating both operational and financial variables, the proposed approach enables a comprehensive understanding of cost dynamics in construction experiments.

Furthermore, the use of a case study involving steel hall assembly provides empirical validation of the framework, demonstrating its applicability in real-world conditions characterized by uncertainty and limited data availability.

4. CASE STUDY

This section presents the case study used to validate the proposed AI-based framework for financial risk assessment and cost prediction in construction experiments. The study is based on a controlled experimental setup involving the assembly of a steel hall structure, designed to simulate real construction conditions while enabling detailed monitoring and data collection.

4.1. EXPERIMENTAL SETUP

The experiment was conducted on a designated site in Žabljak, Montenegro, where a controlled steel hall assembly process was simulated using a scaled structural model, as shown in Figure 2a. The objective of the experimental setup was to replicate key aspects of real construction activities, including material handling, element positioning, and assembly sequencing (Knezevic et al., 2026).

The structural system consisted of a series of columns and beams, representing the primary load-bearing elements of a steel hall. Each element was assigned predefined spatial coordinates based on a surveyed site layout, ensuring consistency and accuracy in positioning (Knezevic & Ostojic, 2026). Figures 2b and 2c show the geodetic marking of reference points and marked ground points serving as initial assembly references. A designated storage area ("warehouse") was defined approximately 15 meters from the assembly location, serving as the starting point for material movement and installation activities. The geometric layout of the structure in AutoCAD is presented in Figure 2(d).

Figure 2: Experimental site and geodetic setup: (a) satellite view of the study location in Vrela, Montenegro; (b) geodetic marking of reference points; (c) marked ground points serving as initial assembly references; and (d) the geometric layout of the steel hall structure with predefined coordinates for columns and beams (source: authors' research)

4.2. MONITORING AND DATA COLLECTION

To enable detailed tracking of construction activities, a location-based monitoring system was implemented using GPS-enabled devices (Ostojic & Knezevic, 2025). Tags were assigned to key entities within the experiment, including structural elements, a worker, and construction equipment, as shown in Figure 3.

Figure 3: GPS-based tracking system applied to the worker (a), equipment (b), and structural element (c) (source: authors' research)

The monitoring system captured spatial and temporal data throughout the assembly process, including movement trajectories, installation times, and interaction events. Special attention was given to the detection of assembly errors, such as incorrect positioning of elements or deviations from the planned installation sequence (Ostojic & Knezevic, 2024).

In addition, safety-related events were recorded, particularly instances where the worker entered predefined proximity zones around machinery, representing potential risk situations. All collected data were timestamped and stored in a structured format, forming the basis for subsequent analysis.

4.3. DATA STRUCTURE AND VARIABLES

The dataset generated during the experiment included both quantitative and event-based variables. Quantitative variables captured measurable aspects of the process, such as assembly duration, number of installed elements, and equipment operating time. Event-based variables included detected errors and safety-related incidents.

Each record in the dataset corresponds to a specific activity or time interval, linking operational data with associated cost components. This structure enables the integration of construction process data with financial analysis, supporting the development of predictive models.

4.4. COST DEFINITION AND MEASUREMENT

The total cost of the experiment was calculated by aggregating labor, equipment, and time-related expenses, as well as additional costs associated with detected errors and safety events. Labor costs were determined based on the duration of worker engagement, while equipment costs were calculated according to machine operating time.

Error-related costs were introduced as penalty factors, reflecting the financial impact of incorrect assembly or rework. Similarly, safety-related events were associated with additional cost components, representing potential delays or risk mitigation measures.

This approach ensures that both direct and indirect cost factors are incorporated into the analysis, providing a comprehensive representation of financial performance in the experimental setup.

4.5. APPLICATION OF THE PROPOSED APPROACH

The collected dataset was used as input for the proposed AI-based framework. The model processed the data to generate predicted cost values and corresponding risk levels for each stage of the assembly process.

The predictions were then compared with actual cost outcomes obtained from the experiment, enabling evaluation of model performance. The framework also supported the identification of key factors influencing cost variability, including assembly efficiency, error frequency, and safety conditions (Ostojic et al., 2024).

4.6. EXPERIMENTAL SIGNIFICANCE

The case study demonstrates the applicability of the presented methodology in a controlled construction environment. By integrating monitoring data with financial analysis and AI-based prediction, the approach provides a comprehensive tool for evaluating cost dynamics and financial risk in construction experiments.

The experimental setup, although scaled, captures essential characteristics of real construction processes, allowing the results to be generalized to similar scenarios. The findings highlight the potential of combining artificial intelligence with experimental monitoring systems to improve financial planning and decision-making in construction projects.

5. RESULTS

This section presents the results of the application of the proposed AI-based framework for cost prediction and financial risk assessment in the steel hall assembly experiment. The analysis focuses on the comparison between predicted and actual costs, as well as the identification of financial risk patterns associated with construction activities. The real-time monitoring interface used during the experiment is presented in Figure 4.

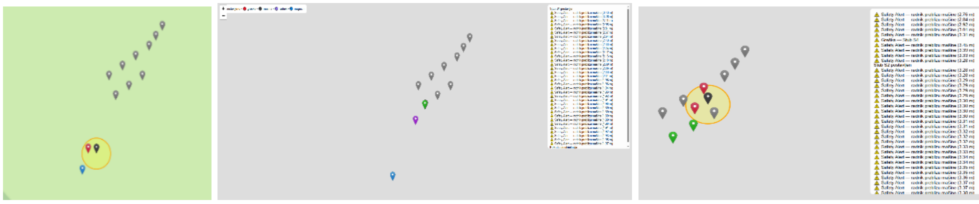

Figure 4: Real-time monitoring interface showing worker and equipment movement with safety alerts and installation status. (source: authors' research)

5.1. PREDICTED VS. ACTUAL COST ANALYSIS

The developed model generated cost predictions based on input variables collected during the experimental assembly process. These predictions were compared with actual costs calculated from recorded labor, equipment usage, and time-related data.

The results indicate that the model achieved a high level of accuracy in estimating total costs, with deviations remaining within an acceptable range for experimental conditions. Minor discrepancies were observed in specific phases of the assembly process, primarily due to unexpected delays and variations in worker performance.

Overall, the predicted cost values demonstrate strong agreement between predicted and actual costs, demonstrating the capability of the model to capture the main cost drivers in construction experiments. As shown in Figure 5, the predicted cost values closely follow the actual cost trend throughout the assembly process, indicating strong model performance.

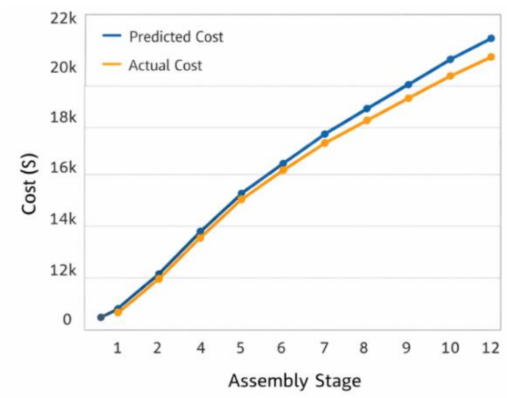

Figure 5: Comparison between predicted and actual costs during the steel hall assembly process (source: authors' research)

5.2. DEVIATION ANALYSIS

To evaluate model performance, deviation between predicted and actual costs was calculated for each stage of the assembly process. The deviation can be expressed as:

$$\Delta C = \frac{C_{actual} - C_{predicted}}{C_{actual}} \times 100\% \quad (2)$$

The analysis showed that deviations were generally low, with higher values occurring in stages characterized by increased uncertainty, such as initial setup and error correction phases. These deviations highlight the influence of dynamic factors that are difficult to fully capture through predictive modeling. Figure 6 presents the variation in cost deviation and associated financial risk levels across different stages of the assembly process.

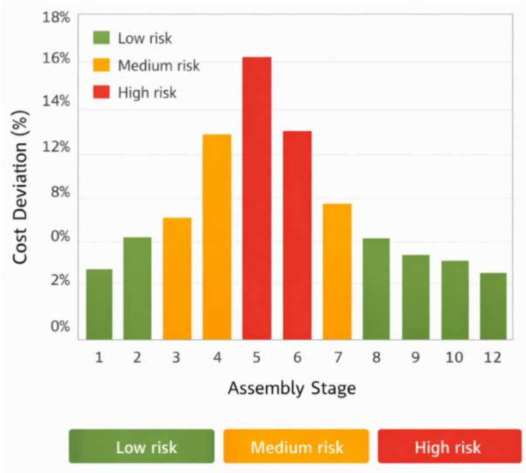

Figure 6: Financial risk classification and cost deviation across different stages of the assembly process (source: authors' research)

5.3. RISK CLASSIFICATION RESULTS

The AI model classified financial risk into three categories: low, medium, and high. The classification was based on deviation thresholds and the presence of error and safety-related events. The results indicate that most assembly stages were associated with low to medium risk levels, reflecting stable execution conditions. High-risk classifications were primarily linked to periods involving detected assembly errors or safety-related events, which introduced additional costs and delays. This classification demonstrates the ability of the model to identify critical phases of the construction process where financial risk is elevated.

5.4. INFLUENCE OF KEY VARIABLES

Analysis of input variables revealed that assembly duration and error occurrence had the most significant impact on cost deviations. Increased installation time directly contributed to higher labor and equipment costs, while errors resulted in additional expenses related to rework and process interruptions.

Safety-related events also influenced cost variability, although their impact was less frequent compared to operational factors. These findings confirm the importance of integrating both operational and event-based variables in financial prediction models.

5.5. MODEL PERFORMANCE EVALUATION

The performance of the AI model was evaluated using standard metrics, including mean squared error (MSE) and prediction accuracy. The results demonstrate that the model provides reliable cost predictions under experimental conditions, with consistent performance across different stages of the assembly process.

The model also showed strong generalization capability, indicating its potential applicability to similar construction scenarios beyond the specific case study.

5.6. SUMMARY OF FINDINGS

The results confirm that this framework is capable of accurately predicting construction experiment costs and identifying financial risk patterns. The integration of AI with construction monitoring data enables a comprehensive analysis of cost dynamics, supporting more informed decision-making.

The findings highlight the importance of incorporating real-time operational data into financial models, particularly in experimental environments characterized by uncertainty and variability.

6. DISCUSSION

The findings indicate that the proposed AI-based framework offers a reliable basis for cost prediction and financial risk assessment in experimental construction settings. The close alignment between predicted and actual costs indicates that the model successfully captures the primary cost drivers associated with steel hall assembly processes.

However, the observed deviations in specific phases of the experiment highlight the inherent uncertainty present in construction environments. These deviations were particularly pronounced during initial setup stages and periods involving error correction, suggesting that early-phase activities and unplanned events play a critical role in cost variability. This finding is consistent with previous studies emphasizing the impact of uncertainty and operational disruptions on construction cost performance (Flyvbjerg et al., 2003; Doloi, 2013).

The results further indicate that assembly duration is one of the most influential factors affecting total cost. Increased installation time directly translates into higher labor and equipment expenses, reinforcing the importance of efficient process planning. In addition, detected assembly errors significantly contributed to cost increases, primarily due to rework and process interruptions. These findings align with existing research identifying productivity and process efficiency as key determinants of construction cost performance (Love et al., 2013).

The integration of risk classification within the predictive model represents an important contribution of this study. By categorizing financial risk levels based on cost deviations and event occurrences, the framework enables early identification of critical phases in the construction process. This capability is particularly valuable for decision-makers, as it supports proactive management of potential cost overruns.

Compared to traditional cost estimation methods, which rely heavily on static data and predefined assumptions, the proposed framework offers a dynamic and adaptive approach. The incorporation of real-time operational data allows for continuous updating of cost predictions, improving responsiveness to changing conditions. This characteristic is especially relevant in experimental construction environments, where uncertainty is higher and data availability is limited.

Despite its advantages, the proposed approach has certain limitations. The experimental setup represents a scaled version of real construction processes, which may affect the generalizability of the results. Additionally, the dataset used for model training is relatively limited compared to large-scale construction projects, which may influence prediction accuracy in more complex scenarios.

Future research should focus on extending the framework to larger and more complex construction systems, as well as integrating additional data sources such as weather conditions, material variability, and workforce experience. The application of more advanced AI models, including deep learning architectures and hybrid approaches, may further improve prediction performance and robustness.

Furthermore, the integration of the proposed framework with digital twin systems and Building Information Modeling (BIM) platforms represents a promising direction for future development. Such integration would enable real-time synchronization between physical and digital environments, enhancing both predictive capabilities and decision support.

Overall, the findings confirm that combining artificial intelligence with financial analysis and construction monitoring provides a powerful tool for improving cost management and reducing financial risk in construction experiments. The proposed framework contributes to bridging the gap between technical monitoring systems and financial decision-making processes, supporting the development of more efficient and resilient construction practices.

7. CONCLUSION

This study presents an artificial intelligence–based framework for financial risk assessment and cost prediction in construction experiments, with a focus on steel hall assembly processes. The proposed approach integrates operational data, cost modeling, and machine learning techniques into a unified analytical model capable of predicting financial outcomes and identifying risk levels.

The results demonstrate that the framework provides reliable cost predictions, with a strong alignment between predicted and actual values. The integration of risk classification further enhances the model's capability by enabling early identification of critical phases associated with increased financial uncertainty. These findings confirm the potential of AI-based approaches to improve cost management and decision-making in construction environments.

The case study highlights the importance of incorporating real-time operational data, including assembly duration, error occurrence, and safety-related events, into financial analysis. By linking construction monitoring systems with cost prediction models, the proposed framework offers a comprehensive tool for evaluating cost dynamics in experimental settings.

In addition to its practical implications, this research contributes to the existing body of knowledge by addressing the gap between technical monitoring and financial analysis in construction experiments. The proposed framework demonstrates how AI can be effectively applied to bridge this gap, supporting both researchers and practitioners in developing more efficient and data-driven construction processes.

Future research should focus on expanding the framework to more complex construction projects and integrating additional data sources to enhance model accuracy and robustness. The combination of AI with digital twin technologies and Building Information Modeling (BIM) systems represents a promising direction for further development.

Overall, the findings suggest that integrating artificial intelligence, financial modeling, and construction monitoring can significantly improve the planning, execution, and evaluation of construction experiments, while also supporting more transparent and sustainable project outcomes.

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