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HYPOTHESIS-VALIDATED CONSTRUCTION ACCIDENT ANALYSIS AND FRAMEWORK FOR POTENTIAL MULTI-SENSOR FUSION WITH 360° CAMERA AND LIDAR

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Abstract. Construction sites are among the most hazardous work environments, with frequent accidents such as falls, entrapments, and collisions. Traditional single-sensor detection systems suffer from occlusions, poor lighting, and limited depth perception, reducing reliability in complex conditions. This study addresses these limitations by proposing a real-time multi-sensor fusion framework integrating a 360° camera and LiDAR. A three-year construction accident dataset was analyzed, and Chi-squared tests and ANOVA ($p < 0.05$) confirmed the statistically significant superiority of the fusion approach over single-sensor systems. Deep learning techniques were applied to enhance real-time detection and prevention capabilities. The results demonstrate that sensor fusion substantially improves detection accuracy, especially in high-risk scenarios such as falls and collisions. This study provides a comprehensive statistical analysis based on national incident records and proposes an AI-driven monitoring framework. The findings offer strong empirical support for multi-sensor fusion as a foundation for next-generation construction site safety systems.

Keywords: construction safety, multi-sensor fusion, 360° camera, LiDAR-based detection, hypothesis testing, chi-squared test.

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1. Introduction

Construction sites are among the most hazardous workplaces, recording the highest accident rates across industries (J. Jeong & J. Jeong, 2021, 2022; Kou & Liu, 2025; Mun et al., 2026). Accidents such as falls, entrapments, crushing, and electric shocks pose severe threats to workers and cause substantial economic losses (Fang et al., 2018a; Lee et al., 2022; Liu et al., 2025; Luo et al., 2018a; Park et al., 2024). Given the inherent complexity and risk, real-time monitoring technologies are essential for proactive accident prevention. However, current systems predominantly rely on single-sensor technologies with known limitations, necessitating more advanced approaches (Kim et al., 2024; Wu et al., 2023).

Recent advances in Artificial Intelligence (AI), Computer Vision, Internet of Things (IoT), and Fusion Sensor Technology have significantly transformed safety management. Real-time object detection and hazard recognition now enable active, real-time interventions (Jeon et al., 2024; Parsons et al., 2024). Nonetheless, challenges such as lighting variation, occlusion, and depth estimation errors continue to undermine detection reliability (Braun et al., 2020; Cheng et al., 2022; Zhou et al., 2021). Multi-sensor fusion has thus emerged as a promising solution for improving detection accuracy and robustness.

Camera-based systems are effective for monitoring PPE compliance and hazardous area intrusions, but their performance deteriorates under poor lighting and occlusions (Braun et al., 2020; Cheng et al., 2022; Zhou et al., 2021). Recent studies have explored more advanced AI-based monitoring frameworks that integrate multimodal sensing and deep learning architectures to improve system robustness and predictive capabilities. For example, generative AI-based multi-modal fusion frameworks have been proposed to enhance anomaly detection and adaptive decision-making in dynamic environments (Bilal et al., 2025a). Similarly, hybrid deep learning architectures combining transfer learning and IoT-based monitoring have been investigated to improve fault diagnosis and real-time system reliability in complex cyber–physical systems. LiDAR systems offer 3D spatial analysis and accurate distance measurement but struggle with object detail interpretation and reflective surface interference (Kim et al., 2022; Satoh, 2022). Other technologies, including RFID, wearables, and IoT-based environmental monitoring, provide supplementary safety insights but cannot comprehensively detect all risks. Therefore, combining sensors is necessary for more effective safety monitoring (Parsons et al., 2024; Wu et al., 2023). Recent research supports the integration of camera and LiDAR to enhance object detection, depth perception, and accident prevention (Jeon et al., 2024; Luo et al., 2018b; Wu et al., 2023). More specifically, the proposed multi-sensor system uses a 360° panoramic camera and a LiDAR sensor as the two primary sensing components. The 360° camera captures wide-angle visual information across the construction site, enabling worker detection, behavior recognition, and hazard-zone monitoring. In contrast, the LiDAR sensor captures depth and spatial location information, enabling distance measurement, object localization, and collision-related risk assessment. These complementary sensing capabilities form the basis of the proposed sensor fusion framework. Recent developments in intelligent sensing systems also highlight the growing integration of IoT architectures and hybrid deep learning models for monitoring complex physical systems. For instance, IoRT-based monitoring frameworks have been proposed to enable real-time fault diagnosis through deep neural networks and transfer learning mechanisms (Bilal et al., 2024). These studies demonstrate the potential of combining sensor networks with AI-based inference models to enhance reliability and scalability in real-world monitoring environments.

Despite these advancements, most existing studies focus on specific domains such as intelligent transportation systems, industrial robotics, or infrastructure monitoring. Their methodologies are not directly applicable to construction safety environments, which involve highly dynamic spatial conditions, frequent occlusions, moving equipment, and diverse accident types. In addition, many recent AI-based monitoring systems prioritize predictive modeling or fault diagnosis rather than real-time hazard detection in complex construction sites. Therefore, there remains a need for a robust sensing framework capable of integrating visual and spatial information to support real-time accident detection and safety monitoring in construction environments (Bilal et al., 2025b; Ullah et al., 2025, 2026; Yousaf et al., 2025).

To address these limitations, this study proposes a real-time construction safety monitoring framework based on 360° camera and LiDAR sensor fusion. By combining semantic visual recognition with precise spatial ranging, the proposed system improves hazard detection reliability under challenging conditions such as occlusion, lighting variation, and complex construction activities. Compared with existing single-sensor approaches, the proposed fusion framework provides more robust accident detection capability and supports adaptive safety monitoring across different construction environments.

However, most existing studies are limited to controlled environments, with few deployed in active construction sites. Additionally, practical implementation challenges, such as real-time. Therefore, this study aims to develop and validate a multi-sensor fusion framework tested in real-world construction environments. The primary objective is to quantitatively evaluate the limitations of single-sensor systems and to propose an advanced framework that integrates a 360° camera and LiDAR for real-time object detection and accident prevention. The main contributions of this study can be summarized as follows: 1) A comprehensive review of existing research to identify limitations and justify the need for sensor fusion; 2) Hypothesis testing (e.g., Chi-squared tests, ANOVA) to statistically validate the superiority of multi-sensor fusion; 3) Development of a real-time fusion framework using 360° camera and LiDAR; and 4) Discussion of cross-industry applicability, including logistics, manufacturing, and smart city safety.

By addressing the limitations of existing safety systems, this study lays the groundwork for next-generation AI-driven accident prevention technologies that can significantly improve occupational safety across sectors.

2. Literature review

2.1. Current research trends in AI-driven construction safety monitoring

The construction industry is widely recognized as one of the most hazardous sectors, driving strong interest in the adoption of AI, computer vision, IoT, and sensor technologies to improve safety outcomes. Recent advances in real-time monitoring systems have focused on object and worker detection, hazardous behavior recognition, collision prevention, and automated surveillance platforms (Fang et al., 2018b; Satoh, 2022; Wu et al., 2023). Beyond single-sensor solutions, researchers are increasingly integrating image processing and 3D spatial perception to expand monitoring capabilities (Kim et al., 2024; Parsons et al., 2024).

Camera-based monitoring systems remain the most widely adopted in practice, leveraging deep learning frameworks such as YOLO, Faster R-CNN, and Mask R-CNN for tasks including PPE compliance, hazard-zone intrusion, and unsafe behavior detection (Cheng et al., 2022; Wu et al., 2023). However, camera systems are vulnerable to lighting variation, occlusion, and narrow fields of view. Enhancements such as infrared imaging, HDR pipelines, and multi-camera arrays alleviate these weaknesses but cannot fully eliminate them (Jeon et al., 2024; Luo et al., 2018b; Zhou et al., 2021).

LiDAR-based systems address complementary challenges by providing precise ranging and spatial mapping for collision avoidance, dynamic hazard detection, and three-dimensional site analysis (Fang et al., 2018c; Jeon et al., 2024). They are resilient under low-light or night-time conditions but encounter difficulties in detecting small objects, managing reflectivity artifacts, and handling high computational costs (Satoh, 2022; Wu et al., 2023).

To overcome these single-modality limitations, researchers have increasingly emphasized Camera–LiDAR sensor fusion. By integrating semantic information from cameras with geometric distance measurements from LiDAR, fusion systems achieve greater precision in object recognition and spatial analysis, while reducing blind spots and improving robustness in complex environments (Parsons et al., 2024; Zhang et al., 2020). Recent studies have extended this approach to 360° fusion architectures for holistic site coverage, enhancing worker tracking and hazard detection (Kim et al., 2022; Jeon et al., 2024).

Despite these advances, the real-world implementation gap remains considerable. Most studies are validated only in controlled laboratory settings, with limited assessment in dynamic construction sites. Persistent challenges include real-time data throughput, sensor installation constraints, and cost considerations. These barriers highlight the need for optimized data fusion algorithms, efficient hardware, and field-based validation to establish the practical effectiveness of AI-driven safety monitoring systems (Wu et al., 2023; Parsons et al., 2024).

Recent studies have increasingly explored the integration of artificial intelligence with multi-modal sensing systems to improve monitoring accuracy and predictive capabilities in complex environments. For example, generative AI-based frameworks have been proposed to integrate heterogeneous sensing data such as video and LiDAR for real-time anomaly detection and behavior modeling in intelligent transportation systems (Bilal et al., 2025a). In industrial environments, deep learning models combined with sensor-based monitoring have been widely applied for predictive maintenance and fault diagnosis of complex mechanical systems (Ullah et al., 2026). Similar AI-driven approaches have also been adopted for infrastructure monitoring tasks such as automated crack detection in transportation infrastructure and sensor-based condition monitoring in industrial robotic systems. These studies highlight the growing potential of AI-driven multi-modal sensing systems to support predictive monitoring and proactive risk management across various engineering domains.

2.2. Identified research gaps in construction safety technology

Despite advancements in construction safety monitoring technology, several research gaps remain:

- Limitations of Single-Sensor Technologies: Existing research primarily relies on either camera-based or LiDAR-based systems for accident detection. However, single-sensor approaches suffer from inherent limitations, such as restricted field of view and reduced detection accuracy under varying environmental conditions (Braun et al., 2020; Zhou et al., 2021). To address these shortcomings, multi-sensor fusion research is essential for enhancing detection performance and system reliability.
- Lack of Real-World Validation in Construction Sites: Most research has been conducted in laboratory settings, with limited evaluation in dynamic and unpredictable construction environments (Fang et al., 2018b; Wu et al., 2023). Previous studies predominantly use preprocessed datasets and controlled conditions, making it difficult to assess system performance in real-world scenarios with diverse external factors. Therefore, field-based validation studies are necessary to evaluate practical applicability and effectiveness.
- Insufficient Coverage of Various Accident Types: Many studies focus on specific accident types, such as falls and entrapments, leading to a lack of comprehensive accident detection systems (Park et al., 2024). A more integrated monitoring framework is required to detect a broader range of construction-related accidents, ensuring improved site safety.

To overcome these research limitations and gaps, it is crucial to quantitatively validate the necessity of fusion sensor technology before developing it. Although this study analyzes construction accident data, the findings do not indicate a significant difference in detection performance between single-sensor and fusion sensor technologies, suggesting that developing a fusion sensor system may not be necessary based on the current dataset. Therefore, this study serves as a preliminary step that conducts quantitative statistical analysis using national accident data. Based on these findings, this study will propose a real-time monitoring system framework integrating 360° camera and LiDAR to address the limitations identified in existing research and explore the potential benefits of fusion sensor technology.

3. Materials and methods

To clarify the research design, the experimental scheme of this study consists of three main stages. First, construction accident data collected from the national Construction Safety Management Integrated Information [CSI] system were classified according to accident type and construction sector. Second, statistical analyses including Chi-squared tests and ANOVA were conducted to investigate the relationships among accident types, construction sectors, and sensor detection technologies. Third, based on the statistical findings, a conceptual multi-sensor fusion framework integrating a 360° camera and LiDAR was developed to address the limitations of single-sensor monitoring systems and enhance accident detection capability. This study aims to effectively prevent construction site accidents and validate the necessity of real-time monitoring systems by systematically collecting and analyzing construction accident data from the past three years. Based on this analysis, we propose a 360° camera and LiDAR-based fusion sensor technology framework to overcome the limitations of existing accident prevention systems and provide practical improvements. To emphasize this need, this chapter provides a detailed explanation of data collection, accident classification, and statistical analysis methodologies. The statistical results obtained from this analysis provide the empirical basis for developing the proposed multi-sensor fusion framework presented in Section 5.

3.1. Construction accident data collection and analysis

To systematically analyze construction site accidents and establish effective prevention strategies, this study collected about 18,000 construction accident cases from the Construction Safety Management Integrated Information system in South Korea over the past three years from 2019 to 2022 (CSI, 2024). The dataset is based on accident reports provided by various institutions and research literature and includes key factors such as facility classification, accident type, cause of occurrence, environmental conditions, use of PPE, and affected objects.

One of the primary challenges in the data collection process was the significant time and resource constraints involved in reviewing the entire dataset. To address this, sampling techniques were applied to select a representative yet manageable subset that ensures both statistical reliability and efficient analysis.

Sampling method

In this study, random sampling was employed to select accident cases, and for a more precise analysis, a combination of proportional sampling and stratified random sampling was applied. As a result, a final sample of 155 accident cases was selected.

Proportional sampling was used to ensure a balanced distribution of accident cases across different construction sectors, including Building, Civil Engineering, Landscape, and Industrial Environments. For instance, if 60% of all accidents occur in the Building sector, the sample was designed to reflect a similar proportion.

Stratified random sampling was applied within each sector to account for the frequency of different accident types, preventing overrepresentation or underrepresentation of specific accident categories. This approach ensured that the selected sample accurately reflected the characteristics of the full dataset.

This sampling methodology enhances data reliability and allows for a more effective analysis of recurring accident patterns in construction sites. Additionally, it minimizes potential biases in the selection process, ensuring that the findings are more representative of real-world construction environments (Cheng et al., 2022).

3.2. Classification of construction accidents based on work breakdown structure

This study applied the Work Breakdown Structure (WBS) to systematically analyze various types of construction site accidents. WBS is a structured approach to categorizing accidents based on construction work phases, allowing for a more precise identification of accidents frequently occurring in specific tasks (J. Jeong & J. Jeong, 2021). The WBS development process was conducted as follows:

First, accident types were defined based on construction accident data collected over the past three years. These accidents were categorized into common construction hazards such as falls, collisions, entrapments, and being struck by an object. Next, each accident type was mapped to its corresponding construction sector, which was classified into four major categories: Building, Civil Engineering, Landscape Architecture, and Industrial Environmental Facilities. Additionally, specific work tasks within each category were further detailed.

Following this classification, the relationship between accident types and construction tasks was analyzed. For instance, falls were most frequently observed in Building construction, where working at heights is common, while collisions were more prevalent in Civil Engineering, where heavy equipment usage is significant. This approach enabled a better assessment of risks associated with specific construction activities.

Furthermore, to explore effective accident detection and prevention strategies, the applicability of sensor technology was evaluated. The study identified camera-based, LiDAR-based, and Camera + LiDAR fusion systems as potential detection technologies. By selecting the most appropriate sensor system for each accident type, the study aimed to enhance accident detection efficiency and establish a more advanced and reliable safety management framework.

Table 1 and Figure 1 categorize various construction accident types into four sectors: Building, Civil Engineering, Landscape Architecture, and Industrial Environmental Facilities. These visuals also illustrate the distribution of accidents detected by Camera, LiDAR, and Camera + LiDAR systems in each sector.

Among the recorded accident types, falls were the most frequent, with 37 cases in the Building sector and 12 in Civil Engineering, along with a few cases in Landscape and Industrial Facilities. This highlights the significant risk associated with elevated workspaces in construction. Additionally, tripping and struck by an object accidents were common, primarily occurring in Building and Civil Engineering construction sites. These accidents are often linked to poor housekeeping, cluttered pathways, or obstacles in movement areas. Traffic accidents and collisions were more prevalent in Civil Engineering and Industrial Facilities, reflecting the higher risks in roadwork and heavy equipment operations. Meanwhile, electric shock was reported only in Industrial Facilities, indicating its association with electrical-related construction work. Entrapment incidents were observed in Building and Civil Engineering sectors, often occurring during structural assembly and installation tasks.

Table 1. Accident types and sensor utilization by construction sector

	Building			Civil Engineering			Landscape Architecture			Industrial Environmental Facilities		
	Camera	LiDAR	Camera + LiDAR	Camera	LiDAR	Camera + LiDAR	Camera	LiDAR	Camera + LiDAR	Camera	LiDAR	Camera + LiDAR
Traffic Accident	1	0	1	2	2	1	0	1	0	0	0	0
Crushing	0	0	1	0	0	0	0	0	0	0	0	0
Entrapment	5	0	3	2	0	0	0	0	0	0	0	0
Fall	37	1	16	12	0	3	0	0	0	1	0	0
Tripping	10	3	6	6	0	2	0	0	0	1	0	0
Struck by an object	14	1	4	0	1	1	0	0	0	1	0	0
Collision	4	2	0	1	0	2	1	2	0	1	0	0
Cutting, Laceration	1	0	0	1	0	0	0	0	0	0	0	0
Electric Shock	0	0	0	0	0	0	0	1	0	0	0	0

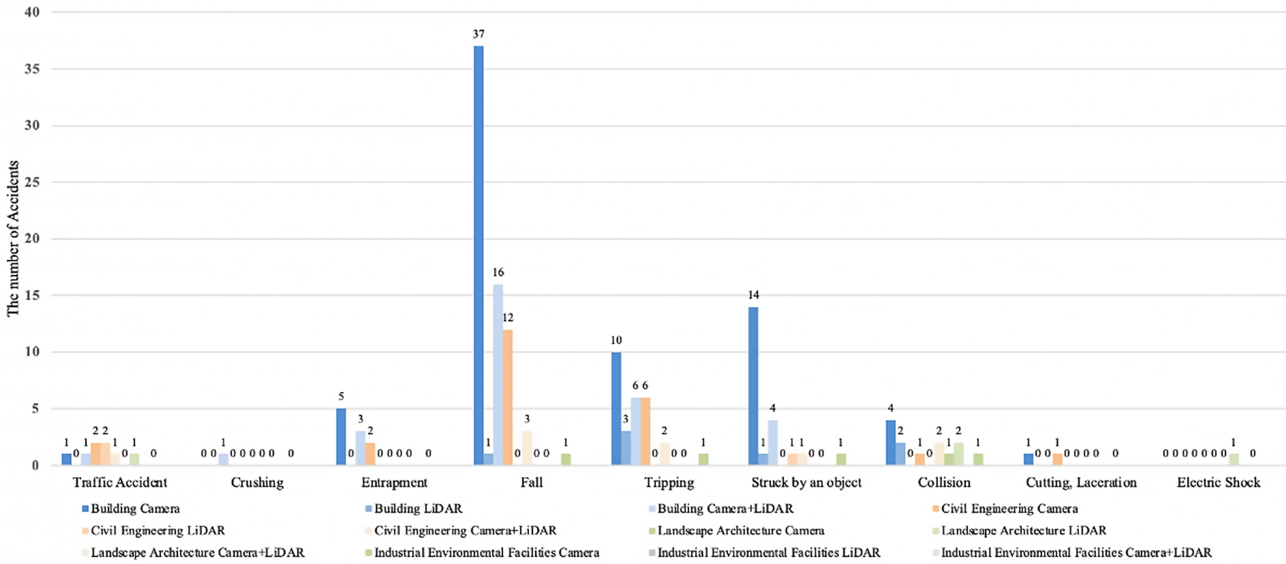

Figure 1. Accident frequency and sensor-based analysis after data sampling by type in construction industry

This study analyzed three years of construction accident data to examine the frequency of accident types and the performance of different sensor technologies. Among 155 analyzed cases, Camera-based systems detected 101 cases (65.2%), LiDAR detected 14 cases (9.0%), and the fusion of Camera + LiDAR detected 40 cases (25.8%). These findings highlight the necessity of fusion sensor technology to compensate for the limitations of single-sensor systems. The fusion of Camera + LiDAR is capable of covering not only the detection areas of single-sensor technology but also the expanded coverage and enhanced accuracy offered by fusion sensor technology. This integration compensates for the limitations of individual sensors, providing a more comprehensive and reliable accident detection system in construction environments.

Among the accidents, falls accounted for the highest frequency (70 cases), with Camera systems detecting 50 of them. Tripping (28 cases) and struck by an object (22 cases) were also frequently reported. Electric shock was the least frequent, with only one recorded case detected by LiDAR. The sector-wise accident distribution showed 110 cases (71.0%) in Building, 36 cases (23.2%) in Civil Engineering, 5 cases (3.2%) in Landscape Architecture, and 4 cases (2.6%) in Industrial Facilities. The higher accident rates in Building and Civil Engineering are likely due to complex work environments and tasks involving high elevations.

In terms of sensor detection performance, Camera-based systems were effective in behavioral analysis and performed well in detecting falls (50 cases), tripping (17 cases), and struck by an object (7 cases). Conversely, LiDAR-based systems excelled in distance and obstacle detection, making them effective for traffic accident (3 cases) and collision (4 cases) detection. The fusion of Camera and LiDAR significantly improved detection performance for falls (19 cases), tripping (8 cases), and struck by an object (5 cases), demonstrating that multi-sensor integration enhances accident detection accuracy.

Based on these findings, accident prevention strategies can be tailored to specific accident types. For instance, installing safety railings and warning systems can help prevent fall accidents, while LiDAR-based obstacle detection systems can be deployed to reduce collision risks. Implementing these technologies can minimize construction site hazards and create a safer work environment.

3.3. Statistical approach for sensor-based accident detection

This study applies various statistical methods to quantitatively analyze construction accident data and validate the performance of sensor-based detection systems. By employing statistical testing, this study examines the relationship between sensor types and accident types and evaluates whether multi-sensor fusion improves accident detection performance (Ma et al., 2020).

3.3.1. Hypothesis testing for sensor performance evaluation

The statistical analysis in this study is based on the following hypotheses:

- **H_1:** A significant relationship exists between accident type and sensor detection technology.
- **H_2:** Multi-sensor fusion (Camera + LiDAR) provides higher detection performance than single-sensor systems (Camera or LiDAR alone).
- **H_3:** Accident type and frequency vary significantly across construction sectors (Building, Civil Engineering, Landscape, Industrial Environmental Facilities).

We employed Chi-Squared Test, ANOVA: Two-Factor With Replication, and ANOVA: Two-Factor Without Replication to test these hypotheses.

3.3.2. Chi-squared test

The Chi-Squared Test was performed to analyze the relationship between accident types and sensor detection technologies. Specifically, we examined the frequency of accident types across construction types and tested whether the differences in accident occurrences were statistically significant.

- Null Hypothesis (**H_0**): There is no significant relationship between construction type and accident type.
- Alternative Hypothesis (**H_1**): A significant relationship exists between construction type and accident type.

Additionally, we compared the frequency of accidents detected by each sensor type (Camera, LiDAR, and Camera + LiDAR) to determine whether detection performance varies depending on the accident type.

- Null Hypothesis (**H_0**): There is no significant relationship between sensor type and accident type.
- Alternative Hypothesis (**H_1**): A significant relationship exists between sensor type and accident type.

3.3.3. ANOVA: Two-factor without replication

The ANOVA: Two-Factor Without Replication test was conducted to evaluate differences in detection performance across accident types and sensor detection methods. This test was used to verify whether detection rates significantly vary depending on the sensor type.

1. Hypothesis on Detection Rate Differences by Accident Type
   - **H_0:** There is no significant difference in detection rates among accident types (e.g., falls, collisions, electric shocks, and etc).
   - **H_1:** Detection rates significantly differ based on accident types.
2. Hypothesis on Detection Rate Differences by Sensor Type and Construction Sector
   - **H_0:** There is no significant difference in detection rates among sensor types (Camera, LiDAR, Camera + LiDAR) and construction sectors (Building, Civil Engineering, Landscape, and Industrial Environment Facilities).
   - **H_1:** Detection rates significantly vary depending on sensor type and construction sector.

3.3.4. ANOVA: Two-factor with replication

The ANOVA: Two-Factor with Replication test was performed to analyze the relationship between construction sectors and accident types. Three primary hypotheses were tested to determine detection rate variations across different construction sectors and potential interaction effects.

1. Hypothesis on Detection Rate Differences by Accident Type
   - **H_0:** There is no significant difference in detection rates among accident types (e.g., falls, collisions, electric shocks and etc.).
   - **H_1:** Detection rates significantly differ depending on accident type.
2. Hypothesis on Detection Rate Differences by Construction Sector
   - **H_0:** There is no significant difference in accident occurrence frequencies across construction sectors (Building, Civil Engineering, Landscape, and Industrial Environmental Facilities).
   - **H_1:** Accident occurrence frequencies vary significantly depending on the construction sector.
3. Hypothesis on the Interaction Between Accident Type and Construction Sector
   - **H_0:** There is no interaction effect between specific accident types and construction sectors. In other words, a particular accident type does not occur more frequently in a specific sector.
   - **H_1:** A specific accident type is more likely to occur in a particular construction sector, indicating a significant interaction effect.

4. Statistical analysis in construction accidents from various point of views

This study analyzed construction accident data from the past three years to examine the relationship between accident types and sensor detection methods while evaluating whether multi-sensor fusion improves detection performance. To achieve this, we applied Camera, LiDAR, and a combined Camera + LiDAR system to collect accident detection data, which was then subjected to statistical analysis. This chapter presents the results of the data analysis and the verification of key research hypotheses.

4.1. Results of sensor types in different construction sectors

Table 2 and Figure 2 summarize 155 detection cases by sensor type (Camera = 101, LiDAR = 14, Camera + LiDAR = 40) and construction sector (Building, Civil Engineering, Landscape, Industrial Environmental Facilities). To test whether detections are independent of sector, we conducted a Pearson chi-square test on the 4×3 contingency table. The test was significant ($\chi^2 \approx 34.03$, $p = 6.65 \times 10^{-6}$), rejecting the null hypothesis of independence. This result does not compare means; rather, it shows that the distribution of detections differs by sector across sensor types.

To localize the departure from independence, we examined standardized residuals (see Figure 3). Values with $|z| \geq 2$ indicate cells contributing strongly to the chi-square statistic. The largest positive residual occurred for Landscape–LiDAR ($z \approx +5.28$), indicating more LiDAR detections in Landscape than expected under independence. Conversely, Landscape–Camera ($z \approx -1.25$) and Landscape–Camera + LiDAR ($z \approx -1.14$) were below expectation. Residuals in Building were small in magnitude (e.g., Building–Camera $z \approx +0.04$; Building–Camera + LiDAR $z \approx +0.49$), suggesting the strong pattern is concentrated in the Landscape sector for LiDAR. Industrial cells showed modest deviations (e.g., Industrial–Camera $z \approx +0.86$; Industrial–Camera + LiDAR $z \approx -1.02$).

Overall, multi-sensor fusion (Camera + LiDAR) accounts for 25.8% of all detections and complements single-sensor coverage, but the strongest sector-specific deviation in this dataset is the over-representation of LiDAR detections in Landscape. These results support the use of sensor–sector tailoring (e.g., prioritizing LiDAR for Landscape environments) and fusion to mitigate single-sensor blind spots.

Referencing Table 3, further validation of detection rates across sensor types (Camera, LiDAR, Camera + LiDAR) was performed using ANOVA: Two-Factor Without Replication.

The ANOVA: Two-Factor Without Replication test was conducted to analyze the variability in detection rates based on accident types, sensor types, and construction sectors.

- Rows Analysis (Accident Type and Detection Rate Differences): The p-value for accident type detection rates was 0.0048 (< 0.05), indicating a statistically significant difference in detection rates among accident types. This confirms that certain accident types have higher detection rates, while others have lower ones. For example, fall accidents exhibited high detection rates, whereas electric shock accidents had significantly lower detection rates.
- Columns Analysis (Sensor Type and Construction Sector Detection Rate Differences).
- The p-value for sensor type and construction sector detection rates was 0.0002 (< 0.05), demonstrating that detection performance varies significantly based on sensor type (Camera, LiDAR, Camera + LiDAR) and construction sector. This suggests that multi-sensor fusion is likely to enhance detection accuracy compared to single-sensor systems. Additionally, the variation in detection performance across different construction sectors implies that certain sensor types may be more effective in specific environments.

Table 2. Analysis of the frequency of accident between sensor and construction types

	Camera	LiDAR	Camera + LiDAR
Building	72	7	31
Civil Engineering	24	3	9
Landscape	1	4	0
Industrial Environmental Facilities	4	0	0
Total	101	14	40

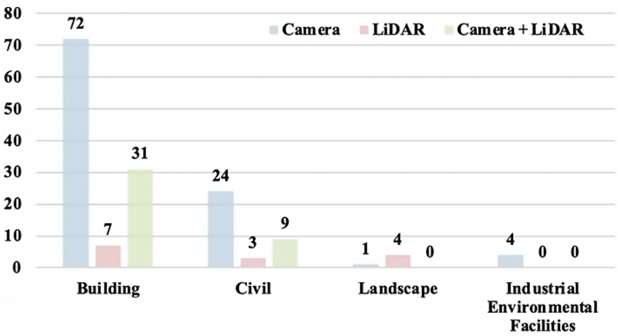

Figure 2. Visualized frequency of accident in terms of construction and sensor types

	Camera	LiDAR	Camera + LiDAR
Building	0.04	–0.93	0.49
Civil	0.11	–0.14	–0.10
Landscape	–1.25	5.28	–1.14
Industrial Environmental Facilities	0.86	–0.60	–1.02

Figure 3. Standardized residuals heatmap for Sensor × Sector contingency table

Table 3. Analysis of ANOVA: Two-factor without replication

Source of Variation	SS	df	MS	F	P-value	F crit
Rows	323.07	8	40.38	3.03	0.004754	2.05
Columns	550.30	11	50.027	3.75	0.000208	1.90
Error	1174.70	88	13.35			
Total	2,048.07	107	–	–	–	–

- F-Value Analysis: The F-value for accident type detection rate differences was 3.03, exceeding the F critical value of 2.05, confirming that detection rates vary significantly depending on the accident type. Similarly, the F-value for sensor type and construction sector detection rate differences was 3.75, exceeding the F critical value of 1.90, verifying that detection performance significantly differs across sensor types and construction sectors.

4.2. Result of construction types and associated accident risks

Table 4 and Figure 4 present accident frequencies across construction sectors. Out of 155 total cases, Building sites accounted for 110 accidents (71.0%), Civil Engineering for 36 (23.2%), Landscape for 5 (3.2%), and Industrial Environmental Facilities for 4 (2.6%). These results underscore the high accident burden in Building and Civil Engineering sectors, highlighting their hazardous working conditions. Building construction is dominated by elevated work environments, resulting in a predominance of fall accidents, while Civil Engineering projects typically involve heavy machinery and large-scale vehicle movements, elevating the risks of collisions and entrapments.

To statistically verify whether accident types are unevenly distributed across sectors, a Pearson chi-square test was conducted on the 9×4 contingency table. The test result was highly significant ($\chi^2 \approx 43.2$, $p = 3.66 \times 10^{-6}$), rejecting the null hypothesis of independence. This indicates that accident types are not evenly distributed across construction sectors.

To identify which cells contributed most strongly to the chi-square statistic, standardized residuals were calculated (Figure 5). Residuals beyond ±2 indicate over- or under-representation relative to expectation. Several notable deviations emerged:

- Building–Fall ($z \approx +0.61$): Although the absolute frequency of falls was highest here (54 cases), the standardized residual was modest, indicating falls were common but consistent with expectation given Building's accident dominance.

Table 4. Analysis of the frequency of accident between construction and accident types

	Building	Civil Engineering	Landscape	Industrial Environmental Facilities
Traffic Accident	2	5	1	0
Crushing	1	0	0	0
Entrapment	8	2	0	0
Fall	54	15	0	1
Tripping	19	8	0	1
Struck by an object	19	2	0	1
Collision	6	3	3	1
Cutting, Laceration	1	1	0	0
Electric Shock	0	0	1	0
Total	110	36	5	4

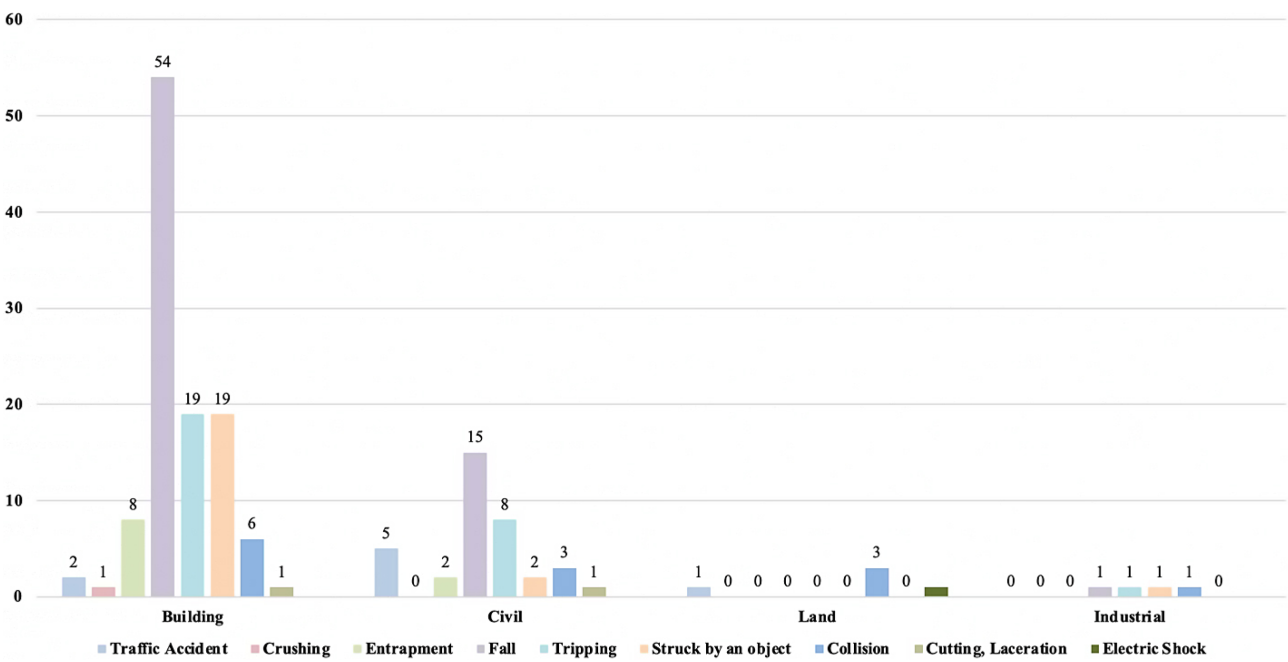

Figure 4. Visualized frequency of accident in terms of construction and accident types

	Building	Civil	Land	Industrial Environmental Facilities
Traffic Accident	−1.54	2.30	1.46	−0.45
Crushing	0.34	−0.48	−0.18	−0.16
Entrapment	0.34	−0.21	−0.57	−0.51
Fall	0.61	−0.31	−1.50	−0.60
Tripping	−0.20	0.59	−0.95	0.33
Struck by an object	0.86	−1.38	−0.84	0.57
Collision	−1.06	−0.01	3.99	1.15
Cutting, Laceration	−0.35	0.79	−0.25	−0.23
Electric Shock	−0.84	−0.48	5.39	−0.16

Figure 5. Standardized residuals heatmap from chi-square analysis of accident type × construction sector

- Civil–Traffic Accident ($z \approx +2.30$): Traffic accidents occurred more often in Civil Engineering sites than expected, consistent with the presence of large-scale machinery and vehicle movement.
- Landscape–Collision ($z \approx +3.99$) and Landscape–Electric Shock ($z \approx +5.39$): Landscape sites recorded more collisions and electrical accidents than expected, despite the small absolute counts. These large positive residuals indicate localized but disproportionate risks.
- Building–Traffic Accident ($z \approx -1.54$) and Land–Fall ($z \approx -1.50$): These negative values show fewer accidents of these types than expected in those sectors.

Together, the analysis reveals that while Building sites dominate in accident counts, Civil Engineering and Landscape sectors exhibit accident-type concentrations that exceed expectations, especially collisions and traffic accidents in Civil, and collision/electric shocks in Landscape.

Referencing Table 5, to further validate differences in accident types and frequencies across construction sectors (Building, Civil Engineering, Landscape, and Industrial Environmental Facilities), an ANOVA: Two-Factor With Replication test was performed.

The ANOVA results indicate statistically significant differences in accident detection rates across construction sectors. The p-value of 0.0015 is below the 0.05 significance level, leading to the rejection of the null hypothesis and confirming that accident detection rates vary significantly across different construction environments. Specifically, Building and Civil Engineering sectors exhibited the highest accident occurrences, whereas Landscape and Industrial Environmental Facilities had relatively lower accident frequencies. This suggests that accident prevention technologies should be more intensively implemented in Building and Civil Engineering sites, where the risks of falls and heavy equipment-related incidents are considerably higher.

The interaction effect between accident type and construction sector was also statistically significant, with a p-value of 0.029, indicating that specific accident types are more prevalent in certain construction environments. For instance, fall accidents were most frequently reported in Building projects, while traffic-related accidents occurred more often in Civil Engineering sites. This confirms that the nature of construction activities directly influences the type of accidents that occur, underscoring the necessity of sector-specific safety strategies.

Since all major factors, including accident type, construction type, and their interaction effects, have F-values exceeding their respective F-critical values, the results confirm that all three variables significantly impact accident detection rates. The findings emphasize the importance of tailored safety measures for each construction sector based on accident type risk profiles. The statistically significant differences suggest that multi-sensor fusion technology should be optimized according to specific accident risks in different environments, ensuring more precise and effective accident detection and prevention.

5. Framework for sensor fusion with 360 degree and LiDAR

5.1. Key components of the multi-sensor fusion framework

Referring to the Figure 6, this study proposes a multi-sensor monitoring framework that integrates a 360° camera and LiDAR to enhance accident prevention and real-time surveillance in construction sites. Traditional Camera-based monitoring systems often suffer from limited fields of view

Table 5. Analysis of ANOVA: Two-factor with replication

Source of Variation	SS	df	MS	F	P-value	F crit
Sample (Differences in accident detection rates across accident types)	18.18	1	18.18	4.75	0.032	3.99
Columns (Differences in accident detection rates across construction sectors)	127.27	10	12.73	3.33	0.0015	1.98
Interaction (Interaction effects between accident types and construction sectors)	83.82	10	8.38	2.19	0.029	1.98
Within	252.5	66	3.83	–	–	–
Total	481.77	87	–	–	–	–

and performance degradation due to lighting variations, whereas LiDAR-based systems face challenges in detecting small objects and are affected by changes in surface reflectivity, leading to reduced accuracy. To overcome these limitations, this study combines both sensors to develop a system capable of more precise object detection and location tracking. The effectiveness and detailed configuration of this framework are presented in Table 6.

5.2. Algorithmic integration of 360° camera and LiDAR data

In this research, framework for the fusion sensor technology is followed by algorithm as shown in Figure 7.

For a reference, the detailed process is as follow.

1. Data Collection: The 360° camera and LiDAR capture real-time construction site footage, detecting the positions of workers and equipment.
2. Preprocessing: The 360° camera image distortions are corrected to generate panoramic views. In addition, LiDAR data noise is removed, and object locations are refined. These preprocessing steps play a crucial role in improving the reliability of the proposed sensor fusion system. Distortion correction ensures that panoramic images generated from the 360° camera maintain accurate spatial relationships, which is essential for consistent object detection and tracking across the wide field of view. Similarly, LiDAR noise filtering reduces measurement errors and removes outliers in point-cloud data, improving the accuracy of object localization and distance estimation. By improving the quality of both visual and spatial data before the fusion stage, these preprocessing procedures help reduce detection errors and enhance the overall stability and performance of the system.
3. Object Detection & Tracking: A YOLO-based deep learning model detects objects in camera footage. LiDAR data is integrated for accurate distance measurement and 3D positioning.
4. Risk Analysis: Detected object movement paths are analyzed to assess proximity to hazardous zones. Warnings are issued when workers approach dangerous areas.
5. Data Storage & Learning: Collected data is stored for deep learning-based pattern analysis. The system continuously improves by updating predictive accident models.
6. Distance-Based Risk Detection: The system measures the distance between objects to evaluate potential hazards. Risk levels are determined based on object relationships and proximity.
7. Alert & Alarm Trigger: When risks are detected, immediate warnings are issued. Visual and auditory alerts are activated, with adjustable intensity based on risk levels.

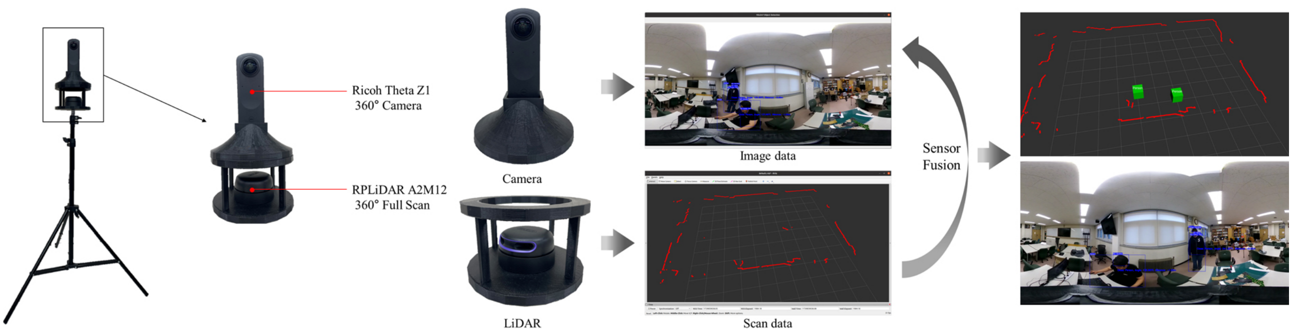

Figure 6. Sensor fusion with 360° camera and LiDAR

Table 6. Sensor fusion framework modules

Module	Description
Data Collection Module	▪ Utilizes 360° camera and LiDAR for real-time video and depth data collection. ▪ The 360° camera provides a comprehensive visual overview of the construction site. ▪ The LiDAR sensor precisely measures object distances and spatial positions.
Data Preprocessing Module	▪ Corrects 360° camera distortions to generate panoramic images. ▪ Removes noise and performs object clustering on LiDAR data. ▪ Applies data filtering to extract meaningful information.
Object Detection & Tracking Module	▪ Implements deep learning-based object detection algorithms (e.g., YOLO, Faster R-CNN). ▪ Detects workers, machinery, and potential hazards in real-time. ▪ Uses 360° camera for visual detection and LiDAR for 3D object localization and distance measurement.
Risk Analysis & Alert System	▪ Analyzes object movement patterns and proximity to assess risk levels. ▪ Activates a real-time warning system when workers enter hazardous zones. ▪ Provides instant alerts and safety notifications to prevent accidents.
Data Storage & Learning Module	▪ Stores collected data in a cloud-based or local database for continuous improvement. ▪ Uses deep learning algorithms to analyze accident patterns and predict high-risk behaviors. ▪ Develops predictive models to detect potential hazards before accidents occur.

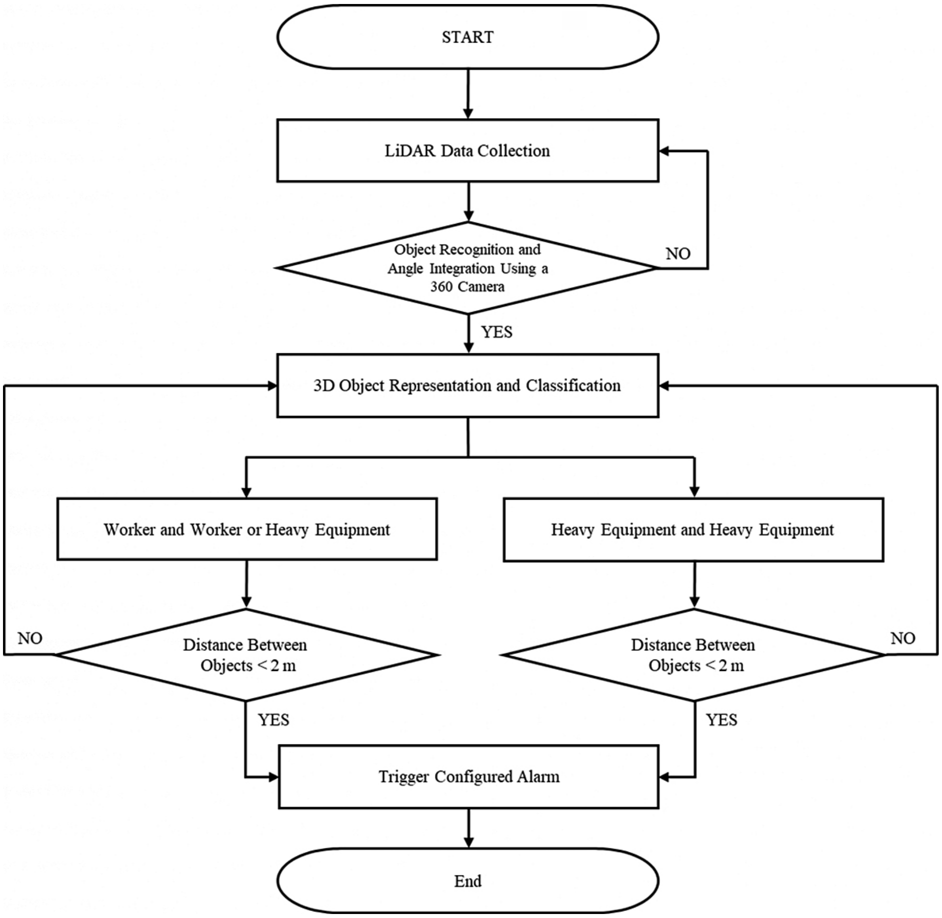

Figure 7. Algorithm of the sensor fusion

8. Continuous Monitoring & Adaptation: Once risks are mitigated, the system resets to normal operation. The system continuously learns and adapts by analyzing new environmental data.

The proposed 360° camera and LiDAR fusion system enhances real-time monitoring capabilities in construction sites, offering a high-precision accident prevention solution.

5.3. Expected outcomes and practical applications of sensor fusion

The proposed 360° camera and LiDAR fusion system is designed to enhance real-time monitoring and provide a more precise accident prevention solution for construction sites. Traditional single-sensor-based systems have limitations, including restricted worker visibility, sensitivity to lighting variations, and challenges in distance measurement. This study addresses these issues by integrating multiple sensors to improve detection accuracy. Rather than simply combining sensors, the framework applies deep learning algorithms to optimize data fusion, ensuring efficient detection and analysis. Additionally, the system strengthens hazard detection and warning functionalities, allowing workers to recognize dangers in real time and take preventive actions.

If implemented, this framework can detect critical accidents such as falls, collisions, and entrapments at an early stage, enabling proactive safety measures. Furthermore, by incorporating deep learning-based continuous improvement, the system can automatically adapt to environmental changes and enhance detection accuracy over time. The key contributions and expected impacts of this study are as follows:

- Enhanced accident detection through sensor fusion
  1) Cameras excel in behavior detection, while LiDAR is superior in distance and position measurement.
  2) The combination of both sensors enables higher accuracy in accident detection.
- Real-time hazard detection and warning system implementation
  1) Analyzes object movement paths and proximity to hazardous zones in real time.
  2) Provides immediate alarms and alerts when workers approach dangerous areas.
- Continuous system improvement using deep learning
  1) Identifies high-risk behaviors in advance to support preventive measures.
- Improved construction site safety and accident prevention
  1) Minimizes accident risks through real-time monitoring.
  2) Prevents collisions between workers and heavy equipment, enhancing overall site safety.

6. Discussion

6.1. Practical implications and technology landscape of multi-sensor fusion for construction safety

This study positions multi-sensor fusion (Camera + LiDAR) as a practical pathway to more precise and robust accident detection in dynamic construction environments. Single-sensor approaches perform well in select scenarios yet show mode-specific blind spots – vision models degrade under poor illumination, occlusion, and limited field of view, while LiDAR is sensitive to surface reflectivity, may miss small objects, and lacks rich appearance cues. By fusing complementary signals, the proposed framework compensates for these weaknesses, enabling safer operations where heavy equipment, moving vehicles, elevation work, and complex site layouts coexist.

Operational use cases are considered as follows.

- Real-time behavior and zone monitoring (Camera): Vision models detect unsafe acts (hazard-zone entry, PPE noncompliance) and scene context (edges, openings, railings) that convey fall risk.
- Proximity and trajectory awareness (LiDAR): Continuous ranging between workers, machinery, and structures supports early collision-risk prediction and geofencing.
- Sensor fusion for collision avoidance: Joint reasoning over image semantics and 3D distance fields improves near-miss detection in blind spots and low-light conditions where unimodal systems struggle.
- Closed-loop alerts: When anomalies are detected, a tiered warning policy (warn → restrict → stop) notifies workers and site managers in real time, reducing incident likelihood.
- Data-log analytics: Accumulated event logs (alerts, near misses, false alarms) support pattern discovery and policy refinement, informing targeted interventions and training.

From a practical deployment perspective, installing sensing systems in active construction environments presents several challenges. Cameras and LiDAR sensors must be strategically mounted to maximize field-of-view coverage while minimizing blind spots caused by equipment, temporary structures, or worker movements. In addition, proper calibration between sensors is required to ensure accurate spatial alignment and reliable data fusion. Environmental factors such as dust, vibration, changing lighting conditions, and dynamic site layouts may also affect sensor performance. Therefore, careful planning of sensor placement, periodic calibration, and robust system design are essential for maintaining reliable monitoring performance in real-world construction sites.

The end-to-end stack integrates on-site sensing (multi-view/360° cameras, LiDAR) with AI-driven real-time processing, optionally backed by a cloud edge for scalable analytics. Practical deployment requires (i) thresholds tuned by sector and work phase (e.g., pour/lift/haul), (ii) site-specific calibration of mounting height/angle and sensor overlap to minimize occlusion, (iii) quality telemetry (illumination, occlusion rate, point-cloud density) to diagnose performance drift, and (iv) resilient operations under bandwidth or power constraints. These controls are essential to translate detection gains into consistent field performance.

Empirically, the fusion framework improves detection reliability over single-sensor baselines by combining semantic recognition with geometric ranging, particularly for collision and near-miss scenarios that challenge unimodal systems. A key advantage of the proposed multi-sensor fusion system lies in the complementary capabilities of the individual sensing modalities. Camera-based systems provide rich visual information that enables worker behavior recognition, worker identification, and hazard-zone monitoring. However, camera systems may struggle with distance estimation and occlusion. In contrast, LiDAR sensors provide precise spatial measurements and depth information, enabling accurate distance estimation and object localization even under poor lighting conditions. By combining these complementary sensing characteristics, the fusion system enhances detection performance across different accident scenarios. For example, fall-related hazards can be detected more reliably using visual cues from cameras, while collision risks between workers and heavy equipment can be more accurately assessed using LiDAR-based distance measurements. This complementary integration explains the improved detection performance observed in the fusion-based system. Construction environments often present challenging conditions for monitoring systems, including lighting variability, occlusion, and complex spatial layouts. For example, construction activities frequently occur during night shifts or in enclosed environments such as tunnels, basements, or interior structural work zones where lighting conditions may be limited. Under such conditions, camera-based systems may experience reduced detection reliability due to insufficient illumination or visual obstruction caused by equipment and temporary structures. In contrast, LiDAR sensors can provide stable depth and spatial measurements regardless of illumination levels. By integrating visual perception from cameras with spatial sensing from LiDAR, the proposed fusion framework can maintain more robust monitoring performance across diverse construction environments. At the same time, the practical adoption of multi-sensor monitoring systems requires consideration of operational trade-offs such as cost, computational latency, power consumption, and maintenance requirements. Nevertheless, the value of sensor fusion is particularly high in construction environments characterized by significant environmental variability (e.g., lighting changes, clutter, and reflective surfaces) and elevated risk exposure (e.g., equipment traffic and work at height). Compared with single-sensor deployments, the proposed Camera–LiDAR fusion approach provides improved detection precision, broader monitoring coverage, and enhanced responsiveness in high-risk operational contexts. In practice, organizations may begin with targeted deployments in priority zones, such as haul routes, lifting areas, or leading edges, followed by incremental system scaling as operational performance and cost–benefit metrics are validated. The observed differences in accident patterns across construction sectors also suggest opportunities for adaptive safety monitoring strategies. For example, building construction environments often involve fall-related hazards associated with work at height, whereas civil engineering projects may present higher risks related to heavy equipment movement and large-scale material handling. In such contexts, multi-sensor monitoring systems could be dynamically configured to prioritize different types of hazard detection depending on the dominant risk profile of the sector. For instance, camera-based monitoring may be emphasized in areas where worker behavior and PPE compliance are critical, while LiDAR-based monitoring may be prioritized in equipment-intensive zones where collision risks are higher. Such adaptive monitoring strategies could support more targeted and responsive safety management in complex construction environments. Another important consideration for real-world deployment is the computational performance of the proposed monitoring system. Multi-sensor fusion systems that integrate deep learning models and heterogeneous sensor data inevitably introduce additional computational load. However, the real-time monitoring requirements of construction safety systems demand timely detection and response to hazardous situations. In practical implementations, lightweight object detection models, optimized inference pipelines, and edge-computing architectures can significantly reduce processing latency. These strategies enable the system to process sensor data streams and generate safety alerts within operationally acceptable response times. In emergency scenarios such as equipment collisions or worker falls, minimizing system latency is critical to ensure that alerts are delivered rapidly enough to support timely intervention and risk mitigation.

6.2. Potential impact on reducing construction accidents

Future research and experimental validation can address key gaps identified in this study. Previous studies relying on single-sensor technologies have faced limitations in detecting certain accident types. This study empirically verifies that multi-sensor fusion, combining camera and LiDAR, effectively compensates for blind spots by enabling detection of hidden workers and analyzing both behavior and distance simultaneously, thus improving detection accuracy.

Additionally, past research has lacked real-time data processing validation. Unlike conventional post-accident analysis systems, the proposed fusion system enables real-time accident prediction and immediate warnings. Integrating deep learning-based behavior pattern analysis could further enhance proactive safety management. Future studies should focus on validating real-time alert systems and refining anomaly detection algorithms in active construction sites. Another technical challenge is the scale problem in vision-based detection, where object size varies with distance, lighting, and angles. Traditional camera systems struggle to recognize distant objects accurately. This study proposes using LiDAR to provide precise distance data, allowing AI-driven calibration of object size to maintain detection accuracy. Future research should optimize deep learning models for sensor fusion and develop adaptive algorithms to address scale variation issues, expanding applications beyond construction to broader industrial safety systems.

7. Conclusions

This study aimed to quantitatively examine the limitations of existing construction safety monitoring approaches and to propose a real-time object detection framework based on multi-sensor fusion using a 360° camera and LiDAR. To validate the necessity of fusion-based sensing technologies, three years of construction accident data were analyzed using statistical methods including Chi-squared tests and ANOVA.

The results demonstrate that the proposed fusion-based framework significantly improves accident detection performance compared with single-sensor approaches. Traditional camera-based systems often suffer from limitations related to lighting conditions, occlusion, and restricted fields of view, while LiDAR-based systems may lack detailed visual information required for recognizing worker behaviors and contextual hazards. By integrating visual perception with spatial sensing, the proposed Camera–LiDAR fusion framework improves detection reliability and enables more robust monitoring in complex construction environments.

This study contributes to construction safety research in two primary ways. First, it provides a quantitative analysis of accident patterns based on construction type, accident type, and sensor type using real-world accident data. Second, it proposes a practical multi-sensor fusion monitoring framework capable of supporting real-time safety management in dynamic construction sites.

Despite these contributions, several limitations remain. The proposed framework has not yet been validated through large-scale field deployments. Future research should therefore conduct real-world experiments to evaluate system performance under diverse operational conditions. In addition, further studies are needed to investigate how sensor configurations and monitoring strategies can be optimized for different construction sectors and accident categories. The interaction between accident types and construction sectors may vary depending on work activities, equipment usage, and spatial conditions. Exploring these variations across more diverse construction environments would help refine adaptive monitoring strategies and improve the effectiveness of sensor-based safety management systems.

Overall, this study provides a foundational step toward the development of practical accident prevention systems based on multi-sensor fusion technologies, supporting safer construction environments and more proactive risk management in construction projects.

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Author contributions

People who contributed to the work are listed in this section along with their contributions: Supervision, SJJ; data collection, KWL and SJJ; statistical analysis, JMJ and KWL; writing original draft of the article, JMJ and KWL; review and editing of manuscript, JMJ, DYG, and YJS.

Disclosure statement

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