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P.P.Eye-Track: Real-Time PPE Detection and Dashboard Analytics for ABC Company Construction Project

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Abstract

Construction sites continue to face persistent PPE non-compliance despite regulatory requirements and routine inspections. Manual monitoring and post-incident CCTV reviews remain reactive and difficult to sustain across multiple work zones, highlighting the need for affordable real-time monitoring tools for small and medium-sized firms. This study developed and evaluated P.P.Eye-TRACK, a YOLOv8-based PPE detection and dashboard analytics system for proactive construction safety monitoring. Using a design and development research approach, the system was trained to detect hard hats, safety vests, and safety shoes from CCTV images, deployed for four weeks at an ABC Company project, and evaluated through validation metrics, field observations, real-time performance testing, usability assessment, cost-benefit analysis, and pilot-final survey comparisons. Results showed strong validation performance, with mAP@0.5:0.95 reaching 85.98%. Field deployment accuracy was moderate at 65.94%, with hard hats detected most reliably and safety shoes most affected by object size, distance, lighting, obstruction, and perspective. Green Zone observations were more accurate than Red Zone, confirming the importance of camera placement. The system met real-time performance thresholds, achieved an excellent SUS score of 90.31, and produced a cost-benefit ratio of 1.55 with a 1.82-year payback period. Findings indicated that P.P.Eye-TRACK is feasible for proactive PPE compliance monitoring, but implementation should include user training, human verification of alerts, expanded safety-shoe datasets, and continuous refinement under varied conditions. This study contributes to SDG 8 by promoting safer workplaces and supports SDG 9 through affordable AI-driven construction safety management.

Keywords: Artificial Intelligence; Construction Safety; Dashboard Analytics; Occupational Safety and Health; Personal Protective Equipment; YOLOv8

1. Introduction

Construction remains one of the most hazardous industrial sectors, as workers are routinely exposed to height-related risks, moving equipment, falling objects, material-handling activities, and constantly changing work zones (International Labour Organization, 2015; Fang et al., 2020). Within this high-risk environment, personal protective equipment (PPE), such as hard hats, safety vests, and safety shoes, continues to serve as a critical layer of protection, particularly when engineering and administrative controls cannot fully eliminate workplace hazards. In the Philippine construction context, PPE compliance is further reinforced by national occupational safety requirements, including the implementing rules of Republic Act No. 11058 and related occupational safety and health standards (Department of Labor and Employment, Bureau of Working Conditions, 2018). Despite these regulatory safeguards, consistent enforcement remains challenging because safety officers must simultaneously monitor multiple work zones while performing documentation, inspection, coordination, and corrective-action responsibilities.

Although many construction sites are equipped with closed-circuit television (CCTV), these systems are commonly used for general surveillance or post-incident review rather than continuous, proactive PPE compliance monitoring. As a result, unsafe acts may only be identified after they have already occurred, limiting the contribution of conventional CCTV to real-time safety management. Advances in computer vision, however, have created opportunities to transform passive video feeds into active safety-monitoring tools. The You Only Look Once (YOLO) family of detectors is particularly relevant to this purpose because it performs object localization and classification in a single processing pass, enabling real-time object detection (Redmon, Divvala, Girshick, & Farhadi, 2016). YOLOv8 extends this capability through a more advanced object detection architecture and implementation features that are well suited for real-time applications (Jocher et al., 2023; Terven, Córdova-Esparza, & Romero-González, 2023).

Building on these technological developments, previous studies have shown that deep learning can support PPE detection and construction safety monitoring (Delhi, Sankarlal, & Thomas, 2020; Liu, Meng, Li, & Hu, 2021). However, important research and implementation gaps remain. First, many existing systems concentrate on a single PPE item, particularly hard hats, rather than detecting multiple PPE classes simultaneously. Second, several studies emphasize algorithmic accuracy but provide limited evidence of actual deployment performance under practical site conditions, such as lighting variation, obstruction, camera perspective, and differences between monitoring zones. Third, fewer systems translate detection outputs into dashboard-based information that safety officers can use for alerts, logs, analytics, and reporting. In addition, commercially available AI safety platforms may be difficult for small and medium-sized enterprises (SMEs) to adopt because of proprietary hardware requirements, subscription costs, and technical complexity.

In response to these gaps, this study developed P.P.Eye-TRACK, an AI-assisted PPE compliance monitoring system that integrates CCTV-based video input, YOLOv8-based multi-class PPE detection, local data logging, and a web-based dashboard for safety officers. This article contributes to construction safety technology in four main ways. First, it evaluates multi-class PPE detection for hard hats, safety vests, and safety shoes. Second, it reports both model validation metrics and actual construction-site deployment accuracy. Third, it assesses dashboard usability using the System Usability Scale (SUS). Fourth, it examines the cost-benefit value of the system for SME-oriented construction safety monitoring. Through these contributions, P.P.Eye-TRACK is positioned not merely as an object detection model but as a practical decision-support system for proactive PPE compliance management.

The findings of this study contribute to the growing body of knowledge on intelligent construction safety systems by demonstrating how affordable computer vision technologies can strengthen proactive occupational safety monitoring while preserving the role of human judgment. The integration of artificial intelligence with dashboard analytics provides construction managers and safety officers with a practical tool for improving PPE compliance, enhancing documentation quality, supporting data-driven safety management, and promoting safer working environments. By making AI-assisted safety monitoring more accessible to small and medium-sized construction firms, this study also supports Sustainable Development Goal 8 (Decent Work and Economic Growth) through the promotion of safer workplaces and Sustainable Development Goal 9 (Industry, Innovation and Infrastructure) through the adoption of innovative digital technologies in the construction industry.

2. Material and methods

2.1. Research design and pilot context

This study employed a Design and Development Research (DDR) approach to guide the development, implementation, evaluation, and refinement of an artificial intelligence-based Personal Protective Equipment (PPE) monitoring system for construction safety. The DDR approach was appropriate because the study centered on the creation of a technological artifact and the systematic assessment of its effectiveness in addressing a practical safety-monitoring problem in an actual construction setting (Richey & Klein, 2013).

Consistent with this approach, the development process followed sequential phases of analysis, design, development, implementation, evaluation, and refinement. These phases provided a structured basis for identifying system requirements, designing the CCTV-to-dashboard workflow, developing the detection model and interface, deploying the system in the field, and refining it based on measured performance and user evaluation. Quantitative system evaluation was then applied to assess model validation performance, actual deployment accuracy, frame rate, latency, usability, cost-benefit indicators, and pilot-to-final survey improvement.

The pilot implementation was conducted over four weeks at an active construction project managed by ABC Company in San Juan, Batangas, Philippines, which provided a realistic environment for evaluating the system under field conditions. ABC Company was treated as an alias to protect the identity and confidentiality of the participating organization. To support site-based monitoring, the researchers installed three study-specific CCTV cameras in strategic work areas, namely the fabrication area, first-floor area, and second-floor area. The system was deliberately limited to the detection of three PPE classes: hard hats, safety vests, and safety shoes. Functions such as facial recognition, biometric identification, worker tracking, mobile applications, accident prediction, and long-term behavioral analysis were excluded from the scope of the study. This boundary was established to ensure that P.P.Eye-TRACK would function as a decision-support tool for safety officers rather than as an automated disciplinary or surveillance system.

Figure 1 presents the overall methodological flow of the study, showing how the Design and Development Research approach was operationalized from problem analysis to system refinement. The flowchart illustrates the sequential connection among requirements analysis, system design, YOLOv8 model development, CCTV-based implementation, quantitative performance evaluation, usability assessment, cost-benefit analysis, and final refinement. By organizing these activities into a single process, the figure clarifies that the evaluation of P.P.Eye-TRACK was not limited to model accuracy alone but also included field deployment performance, user-centered dashboard assessment, and practical feasibility for construction safety monitoring.

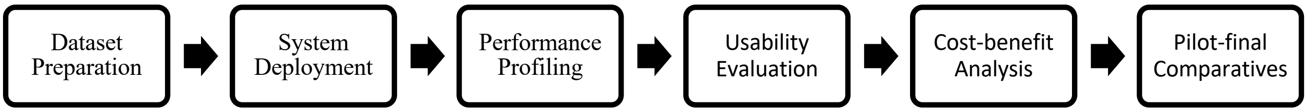

Figure 1 Methodology flowchart used for system evaluation

2.2. System architecture and workflow

P.P.Eye-TRACK was developed using CCTV-to-dashboard architecture that integrates video capture, frame processing, object detection, data storage, and dashboard-based safety reporting into a single monitoring workflow. CCTV cameras captured footage from designated monitoring points within the construction site, while OpenCV extracted frames from the video stream for analysis. The extracted frames were then processed by the YOLOv8 model to detect the target PPE classes, namely hard hats, safety vests, and safety shoes. PHP 8.2 supported the dashboard operations, while MySQL stored violation logs, timestamps, monitoring points, captured records, and related system outputs. Through this integrated workflow, the dashboard presented live or recent monitoring feeds, PPE status cards, violation alerts, detection logs, analytics, monitoring point comparisons, report-generation functions, raw image records, and administrator controls.

The architecture was intentionally designed to function as a decision-support system rather than as an automated disciplinary mechanism. When the system detected possible PPE non-compliance, the dashboard generated an alert and stored the corresponding violation record for further review. Safety officers remained responsible for examining the record, validating the incident, and determining the appropriate corrective action based on site context and professional judgment. This design preserved human oversight while reducing the burden of continuous manual monitoring and improving the availability of structured safety documentation for inspection, reporting, and follow-up action.

Figure 2 illustrates the operational workflow of P.P.Eye-TRACK from CCTV input to dashboard-supported safety action and evaluation. The figure shows how site footage is converted into analyzable frames, processed through YOLOv8-based PPE detection, and translated into dashboard outputs such as alerts, logs, monitoring summaries, and records for safety officer reviews. By presenting these components as an end-to-end process, the figure clarifies the connection between technical detection and practical safety management, emphasizing that the system supports evidence-based decision-making rather than replacing professional judgment.

Figure 2 System workflow of P.P.Eye-TRACK from CCTV input to dashboard-based safety action and evaluation

This workflow also demonstrates the importance of linking the technical components of the system with the actual decision-making needs of construction safety personnel. Rather than treating object detection as an isolated computational task, P.P.Eye-TRACK organizes detection results into usable records that can support monitoring, validation, documentation, and reporting. This integration is essential in construction settings because safety officers require not only automated alerts but also contextual information that can help them determine whether an observed violation is valid, recurring, location-specific, or related to camera visibility and site conditions.

2.3. Dataset Preparation and Model Training

Video frames were extracted from CCTV footage captured at the construction site to establish an image dataset that reflected actual monitoring conditions. The extracted frames were manually annotated using Roboflow, with hard hats, safety vests, and safety shoes identified as the target PPE classes. Bounding-box annotations were used because the study required both classification of PPE items and localization of their positions within the image. The annotations followed the

Common Objects in Context (COCO) format, which is widely used for object detection datasets and supports standardized training and evaluation procedures (Lin et al., 2014). After annotation, the dataset was divided into 70% training, 20% validation, and 10% testing subsets to ensure that the YOLOv8 model could be trained, tuned, and evaluated using separate data partitions. Model-level performance was assessed using precision, recall, F1-score, mAP@0.5, and mAP@0.5:0.95 because these metrics jointly evaluate classification correctness and bounding-box localization quality (Goodfellow, Bengio, & Courville, 2016; Padilla, Passos, Dias, Netto, & da Silva, 2021).

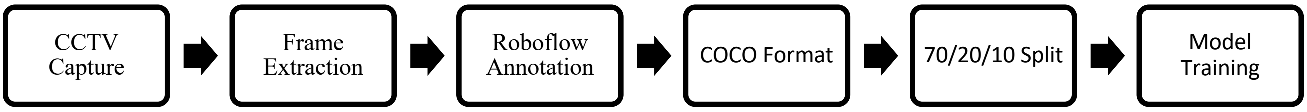

Figure 3 Dataset preparation process

Figure 3 summarizes the dataset preparation process followed in the study, beginning with the extraction of CCTV-based image frames and proceeding to manual annotation, class labeling, dataset formatting, and data partitioning. The figure provides a visual representation of how raw construction-site footage was transformed into a structured object detection dataset suitable for YOLOv8 training and validation. This process was essential because the quality and consistency of the annotated dataset directly influenced the ability of the model to recognize PPE items under practical construction-site conditions.

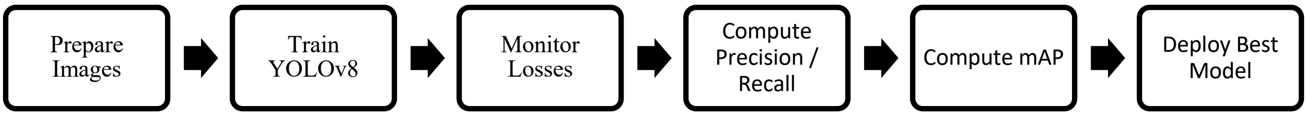

Figure 4 Training and validation workflow

Figure 4 presents the training and validation workflow used to develop and assess the YOLOv8 detection model. The workflow shows how the prepared dataset was processed through model training, validation, metric computation, and performance review before deployment. By linking training procedures with validation outputs, the figure clarifies that model development was treated as an iterative process in which detection performance was examined before applying the system to actual construction-site monitoring.

The YOLOv8 model was trained for 100 epochs using a standard configuration with an image resolution of 640 × 640 pixels, a batch size of 16, and an initial learning rate of 0.01 with cosine decay scheduling. To strengthen model generalization across varying construction-site conditions, data augmentation techniques such as horizontal flipping, brightness adjustment, mosaic augmentation, and random scaling were applied during training. These augmentation procedures were important because PPE visibility in actual sites may be affected by changing illumination, worker movement, partial obstruction, viewing angle, and differences in object size. Training was conducted in a GPU-enabled computing environment with Intel(R) Iris(R) Xe Graphics, 16.0 GB RAM, and an 11th Gen Intel(R) Core (TM) i5-1155G7 processor to support efficient model convergence and stable performance. The selected training parameters were intended to balance computational efficiency with detection accuracy, which is necessary for developing a system that can later be evaluated under real-world construction monitoring conditions.

2.4. Deployment Validation and Detection Zones

Actual deployment validation was conducted separately from model validation to determine whether P.P.Eye-TRACK remained reliable under construction-site conditions. A total of 8,323 CCTV-captured images were generated during deployment. From this population, 368 images were randomly selected for manual validation. Because each image was evaluated for three PPE classes, the validation produced 1,104 class-level observations. A detection was recorded as accurate when the PPE item was correctly classified and properly localized. It was recorded as inaccurate when the system missed the PPE item, produced an incorrect classification, duplicated a detection, or localized the object poorly.

To interpret the influence of camera coverage, each monitoring view was divided into a Green Zone and a Red Zone as shown in Figure 5 and 6. The Green Zone represented the more favorable detection area with clearer worker visibility, while the Red Zone represented less favorable conditions caused by distance, partial obstruction, lower object visibility, or limited camera perspective. Camera placement and visibility were treated as important because CCTV monitoring performance is affected by camera height, viewing angle, distance, resolution, layout, and object visibility (Choi & Lee, 2015; Kim, Ham, Chung, & Chi, 2019; Hao et al., 2022).

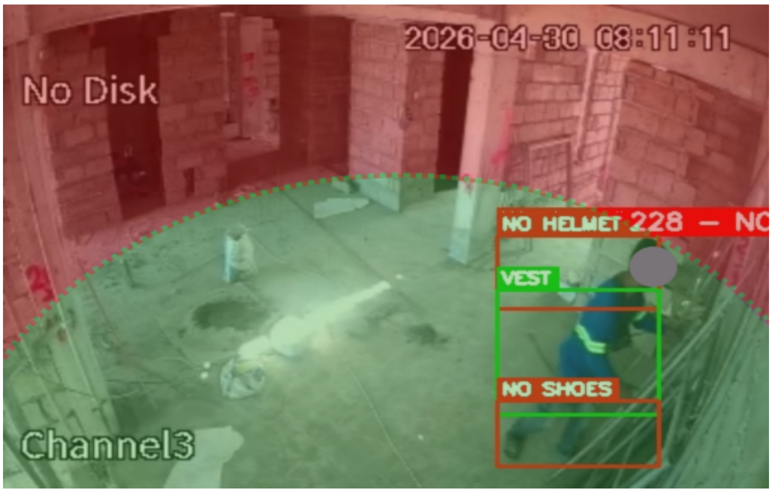

Figure 5 Green Zone visualization

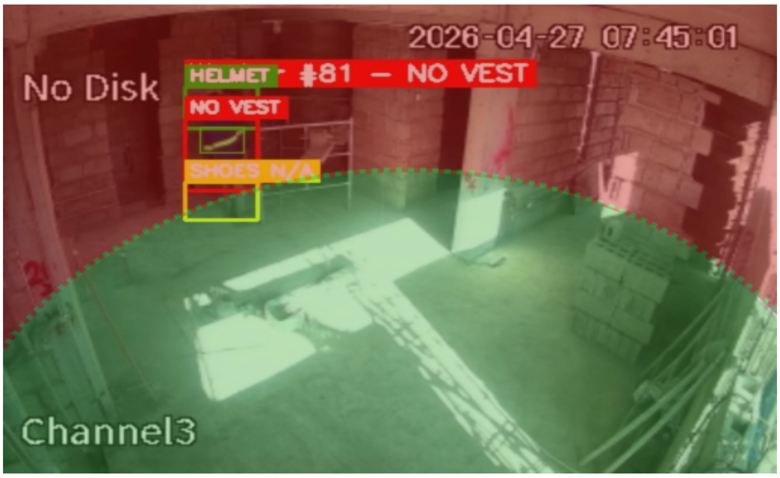

Figure 6 Red Zone visualization

2.5. System performance evaluation

System performance was evaluated using frames per second (FPS) and latency logs to determine whether P.P.Eye-TRACK could support real-time PPE monitoring under construction-site conditions. FPS reflected the number of video frames processed by the system per second, whereas latency represented the time delay between frame input and detection output. For this study, real-time performance was assessed using average threshold values of at least 20 FPS and no more than 150 ms latency. However, the evaluation did not rely solely on system-reported averages; instantaneous FPS and latency values were also examined to determine whether short-term processing instability occurred during deployment. This distinction was important because edge-based object detection systems may satisfy average throughput requirements while still experiencing momentary performance drops caused by processing load, scene complexity, buffering, camera feed variation, and hardware limitations (Lema, Usamentiaga, & García, 2024; Alqahtani, Cheema, Rodriguez, & Toosi, 2024).

2.6. Dashboard usability and survey evaluation

Dashboard usability and system acceptability were evaluated by eight key personnel from ABC Company who were directly involved in operating, observing, supervising, or assessing P.P.Eye-TRACK during deployment. The respondents included safety officers, engineers, architects, foremen, and construction personnel, thereby providing perspectives from both technical and site-based users. To obtain a structured assessment of the dashboard, the evaluation combined structured observation, a five-point Likert-type instrument, and the System Usability Scale (SUS). The SUS is a ten-item usability instrument that generates a standardized score ranging from 0 to 100 (Brooke, 1996). Scores above 68 are commonly interpreted as above average, while higher scores indicate stronger perceived usability and user acceptance (Bangor, Kortum, & Miller, 2008; Sauro & Lewis, 2016). In addition, the reliability of the dashboard evaluation variables was examined using Cronbach's alpha to determine the internal consistency of the survey items (Tavakol & Dennick, 2011).

To assess whether the system refinements improved user evaluation, the pilot and final survey results were compared using the same eight respondents. The pilot survey served as the baseline assessment before refinement, whereas the final survey was administered after modifications were made based on deployment observations and user feedback. Six assessment themes were examined: detection accuracy, system performance, dashboard usability and functionality, UI/UX design, cost-benefit, and overall assessment. Because the same respondents rated the system before and after refinement using Likert-type responses, the Wilcoxon Signed-Rank Test was used as a paired non-parametric procedure appropriate for comparing related ordinal data (Wilcoxon, 1945; Sullivan & Artino, 2013).

2.7. Data analysis

Data analysis was conducted using descriptive and inferential statistical procedures aligned with the technical, usability, and economic evaluation objectives of the study. Descriptive statistics were first used to summarize detection accuracy, FPS, latency, usability mean scores, and cost-benefit indicators. To examine whether detection outcomes differed according to deployment-related factors, chi-square tests of independence were applied to PPE class, deployment area, detection zone, and the area-PPE class combination (McHugh, 2013). Where applicable, Cramer's V and odds ratios were reported to describe the practical effect size and strength of association among categorical variables (Ben-Shachar, Patil, Thériault, Wiernik, & Lüdecke, 2023). In addition, a one-sample t-test was used to compare the mean System Usability Scale (SUS) score with the benchmark score of 68. Economic evaluation was conducted through cost-benefit analysis, which included total system cost, annual benefits, net benefits, return on investment (ROI), cost-benefit ratio, break-even period, and payback period. This financial assessment was included because occupational safety economics recognizes that safety interventions can generate value not only through direct cost reductions but also through operational improvements and more efficient resource use (Leigh, 2011; Grimani, Bergström, Casallas, Aboagye, Jensen, & Lohela-Karlsson, 2018).

The interpretation of the results was guided by both statistical significance and practical relevance to construction safety implementation. Rather than relying solely on p-values or aggregate performance indicators, the analysis considered whether the findings were meaningful for actual site monitoring, safety officer decision-making, system usability, and SME adoption. This approach was important because the effectiveness of an AI-assisted safety system depends not only on model accuracy but also on deployment stability, worker visibility, dashboard interpretability, cost feasibility, and the ability of safety personnel to apply the generated information within existing safety management procedures.

2.8. Ethical considerations

The system excluded facial recognition, biometric identification, and worker identity tracking. CCTV feeds were used only for PPE compliance detection within designated work zones. Site access was authorized, participants were informed about the research purpose, and collected data were used only for system evaluation. This privacy-preserving design aligned with data minimization and transparency principles under the Philippine Data Privacy Act (Republic Act No. 10173, 2012). The study treated P.P.Eye-TRACK as a monitoring and documentation aid for safety officers rather than a replacement for human judgment or due process.

3. Results and discussion

3.1. YOLOv8 model validation

The model-level validation results showed strong detection performance across all standard metrics. Table 1 summarizes the YOLOv8 validation output.

Table 1 YOLOv8 validation performance metrics

Metric	Value	Interpretation
Precision	97.38%	Excellent
Recall	94.15%	Excellent
F1-score	95.74%	Excellent
mAP@0.5	97.30%	Excellent
mAP@0.5:0.95	85.98%	Very high

Note. Precision indicates the proportion of correct positive detections, recall indicates the proportion of actual PPE instances detected by the model, and F1-score represents the balance between precision and recall. mAP@0.5 and mAP@0.5:0.95 summarize detection accuracy based on bounding-box localization thresholds, with higher values indicating stronger object detection performance.

The mAP@0.5:0.95 value of 85.98% exceeded the study benchmark of 80%, indicating that the trained detector maintained strong performance even when evaluated under stricter localization thresholds. This result suggests that the model was not only capable of identifying the target PPE classes but also of producing bounding boxes with acceptable localization quality. The progression of the validation metrics from the first epoch to the final epoch further indicates effective model learning during training. Precision increased from 0.92% to 97.38%, recall improved from 42.20% to 94.15%, mAP@0.5 rose from 15.08% to 97.30%, and mAP@0.5:0.95 increased from 8.39% to 85.98%. These improvements support the technical feasibility of using YOLOv8 for multi-class PPE detection involving hard hats, safety vests, and safety shoes. However, model validation results should be interpreted as only one level of system assessment because actual construction-site deployment introduced additional visual and operational challenges, including lighting variation, occlusion, worker movement, camera angle differences, and object-size limitations.

3.2. Actual deployment detection accuracy

Actual deployment validation produced lower but more realistic performance than model validation.

Table 2 Actual deployment detection accuracy by PPE class

PPE Class	Accurate	Inaccurate	Total	Accuracy	Interpretation
Hard hat	292	76	368	79.35%	Highest class accuracy
Safety vest	258	110	368	70.11%	Moderate to strong accuracy
Safety shoes	178	190	368	48.37%	Main detection limitation
Overall	728	376	1,104	65.94%	Moderate field performance

Note. Accuracy was computed from 368 randomly selected deployment images, with each image evaluated across three PPE classes, resulting in 1,104 class-level observations. A detection was classified as accurate when the PPE item was correctly identified and properly localized, while inaccurate detections included missed items, incorrect classifications, duplicate detections, or poor localization.

Table 2 presents class-level accuracy based on 368 randomly selected images and 1,104 class-level observations. Hard hats achieved the highest deployment accuracy at 79.35%, followed by safety vests at 70.11%. Safety shoes obtained the lowest accuracy at 48.37%. This result is technically expected because safety shoes are smaller, located near the ground, frequently obstructed by materials or body posture, and more sensitive to camera distance and lower-frame visibility. Object detection performance depends not only on class recognition but also on bounding-box localization and sufficient object visibility (Padilla, Passos, Dias, Netto, & da Silva, 2021).

Table 3 Statistical summary of deployment detection results

Metric	Value	Results	Interpretation
PPE class vs outcome	chi-square=82.890; df=2	p < .001; Cramer V=0.274	Significant class effect
Area vs outcome	chi-square=16.052; df=2	p < .001; Cramer V=0.121	Moderate combined effect
Zone vs outcome	chi-square=19.883; df=1	p < .001; OR=1.89	Green Zone advantage

Note. Chi-square tests were used to examine whether detection outcomes differed by PPE class, deployment area, and monitoring zone. Cramer's V indicates the strength of association for categorical comparisons, while the odds ratio (OR) describes the likelihood of accurate detection between zones. A p-value below .05 indicates a statistically significant association.

The chi-square test presented in Table 3 indicated a statistically significant association between PPE class and detection outcome, $\chi^2(2, N = 1{,}104) = 82.890$, $p < .001$, with Cramer's V = 0.274. This result shows that detection accuracy differed significantly across hard hats, safety vests, and safety shoes, rather than occurring uniformly across the three PPE categories. The pattern of results suggests that P.P.Eye-TRACK was more reliable in detecting head-level and upper-body PPE than lower-body PPE, which is consistent with the lower field accuracy observed for safety shoes. This limitation may be attributed to the smaller physical size of safety shoes, their ground-level position, partial obstruction from site materials or worker posture, and reduced visibility at greater camera distances. Future system improvement should therefore prioritize the expansion of safety-shoe training images, lower-body camera calibration, higher-resolution views of walking zones, and data augmentation strategies that account for shadows, occlusion, and ground-level clutter.

3.3. Deployment area and detection zone effects

Detection performance also differed across deployment areas and monitoring zones, indicating that field accuracy was shaped not only by the PPE class being detected but also by the visual conditions of each site location. Among the three deployment areas, the fabrication area achieved the highest accuracy at 72.88%, followed by the second-floor area at 69.43%, while the first-floor area recorded the lowest accuracy at 58.81%. The chi-square test summarized in Table 3 showed a statistically significant association between deployment area and detection accuracy, $\chi^2(2) = 16.052$, $p < .001$, although the effect size was weak (Cramer's V = 0.121). More importantly, the combined area-PPE class analysis produced the strongest association, $\chi^2(8, N = 1{,}104) = 162.523$, $p < .001$, Cramer's V = 0.384. This result suggests that detection performance was influenced by the interaction between the type of PPE being detected and the site-specific visual conditions, such as camera distance, angle, lighting, obstruction, and worker visibility within each monitoring area.

Table 4 Detection accuracy by monitoring zone

Zone	Accurate	Inaccurate	Accuracy
Green Zone	582	255	69.53%
Red Zone	146	121	54.68%

Note. The Green Zone refers to monitoring areas with more favorable camera coverage, clearer worker visibility, and better detection distance, while the Red Zone refers to areas with less favorable visibility, greater distance, obstruction, or limited camera perspective. Accuracy was computed as the proportion of accurate detections relative to the total detections within each monitoring zone.

Table 4 indicates that detection accuracy was higher in the Green Zone at 69.53% than in the Red Zone at 54.68%, demonstrating the influence of monitoring-zone conditions on field performance. The difference between zones was statistically significant, $\chi^2(1) = 19.883$, $p < .001$, with Cramer's V = 0.134 and an odds ratio of 1.89. This finding suggests that accurate detection was nearly twice as likely to occur in the Green Zone as in the Red Zone. The result reinforces the importance of camera placement, effective detection distance, worker visibility, and field-of-view planning in the successful deployment of AI-assisted PPE monitoring systems. For practical adoption, construction firms should therefore avoid treating AI detection as independent from camera design; instead, CCTV layout, camera angle, detection distance, and zone calibration should be planned as integral components of the overall safety monitoring system.

3.4. Real-time system performance under construction conditions

Table 5 Average system performance metrics

Area	Mean FPS Average	Mean Latency Average (ms)	Interpretation
Fabrication	31.74	56.08	Passed average FPS and latency
First floor	343.30	60.22	Passed; instantaneous spikes
Second floor	228.97	55.38	Passed; low instantaneous FPS

Note. FPS refers to the number of video frames processed by the system per second, while latency refers to the delay between frame input and detection output. The system was considered to have passed the average real-time threshold when FPS was at least 20 and latency was not more than 150 ms. Interpretations are based on system-reported average performance and should be read together with the instantaneous performance logs discussed in the text.

Table 5 presents the comparative FPS and latency results across the three deployment areas, providing an indication of how P.P.Eye-TRACK performed under actual construction-site monitoring conditions. The system-reported average FPS exceeded the minimum threshold of 20 FPS in all areas, while the system-reported average latency remained below the maximum threshold of 150 ms. Based on these average values, the system met the established real-time performance requirements. However, the instantaneous performance logs showed that real-time processing was not consistently stable across all monitoring areas, indicating the need to distinguish between average system performance and moment-to-moment operational reliability.

Among the deployment areas, the fabrication area demonstrated the most stable latency performance, with all sampled instantaneous latency values remaining within the 150 ms threshold. In contrast, the first-floor and second-floor areas recorded latency spikes, and only 3 of the 15 instantaneous FPS values met or exceeded the 20 FPS threshold. These results suggest that P.P.Eye-TRACK satisfied the real-time requirements when evaluated using average performance indicators but remained only partially stable during moment-to-moment field processing. This distinction is important for real-time safety monitoring because temporary drops in FPS or increases in latency may affect the timeliness of alerts and the responsiveness of safety officers. The observed performance variation may have been influenced by hardware load, camera feed quality, buffering, worker movement, scene complexity, and occlusion. Similar trade-offs have been noted in edge-device object detection studies, which emphasize that detection accuracy must be balanced with inference time, processing speed, and available computational resources (Lema, Usamentiaga, & García, 2024; Alqahtani, Cheema, Rodriguez, & Toosi, 2024).

3.5. Dashboard usability and safety officer adoption

The dashboard served as the primary interface for translating AI-based detection outputs into actionable safety management information. It consolidated real-time detection views, PPE violation alerts, violation logs, PPE status cards, analytics, monitoring point comparisons, report-generation functions, raw image records, and administrator controls into a single monitoring environment. The evaluation results indicate that users perceived the dashboard positively, with the dashboard usability category obtaining an overall mean of 4.88, interpreted as strongly agree. Similarly, UI/UX design obtained an overall mean of 4.93, while the overall system assessment reached 4.81. These findings suggest that the dashboard was considered clear, functional, and useful for supporting PPE compliance monitoring during deployment. The reliability results further strengthen this interpretation, as Cronbach's alpha values were 0.94 for dashboard usability, 0.94 for UI/UX design, and 0.97 for overall assessment and recommendations, indicating strong internal consistency among the evaluation items.

Table 6 Statistical summary of deployment detection results.

Evaluation Area	Result	Interpretation
Dashboard usability	4.88	Strongly agree
UI/UX design	4.93	Strongly agree
Overall assessment	4.81	Strongly agree
SUS score	90.31	Excellent

Note. Dashboard usability, UI/UX design, and overall assessment were evaluated using a five-point Likert-type scale, with higher mean scores indicating stronger agreement and more favorable user evaluation. The SUS score ranges from 0 to 100, with higher scores reflecting stronger perceived usability. The results indicate that users rated the dashboard and overall system positively during deployment.

The SUS evaluation produced an overall score of 90.31, with individual respondent scores ranging from 80.00 to 95.00. A one-sample t-test further confirmed that the mean SUS score was significantly higher than the benchmark score of 68, $t(7) = 10.20$, $p < .001$. This result indicates excellent perceived usability and suggests that the dashboard was generally easy to understand, navigate, and apply during PPE compliance monitoring. From an operational perspective, the high SUS rating shows that safety officers and site personnel were able to interpret the dashboard outputs clearly and use them as meaningful safety management information. This finding is important because the practical value of an AI-based detection model depends not only on its technical accuracy but also on whether its outputs can be understood, verified, and acted upon by the personnel responsible for safety enforcement.

3.6. Cost-benefit analysis

In addition to technical feasibility, financial viability plays a critical role in determining whether intelligent safety systems can be adopted by construction companies, particularly small and medium-sized enterprises (SMEs). To evaluate economic feasibility, a cost–benefit analysis was performed using the total implementation cost and the projected operational savings generated through the deployment of P.P.Eye-TRACK.

Table 7 Statistical summary of deployment detection results

Indicator	Value	Interpretation
Total system cost	PHP 203,451	Low initial investment
Total benefits without revenues	PHP 315,000	Strong benefit generation
Net benefits	PHP 111,549	Positive financial gain
ROI	55%	Good return
Cost-benefit ratio	1.55	PHP 1.55 benefit per PHP 1 spent
Break-even period	7.75 months	Fast recovery using direct savings
Payback period	1.82 years	Recovery using net benefits

Note. Cost-benefit indicators were computed based on the estimated implementation cost and measurable annual benefits identified for the pilot deployment. ROI represents the net return relative to total system cost, while the cost-benefit ratio indicates the amount of measurable benefit generated for every peso spent. Break-even and payback periods describe the estimated time required to recover the investment under the assumptions used in the study.

Table 7 summarizes the financial viability indicators used to assess the economic feasibility of P.P.Eye-TRACK. The total system cost amounted to PHP 203,451, which consisted of PHP 170,451 in non-recurring costs and PHP 33,000 in recurring costs. Against this investment, the total measurable annual benefits without revenues were estimated at PHP 315,000, resulting in net benefits of PHP 111,549. These figures indicate that the system generated positive measurable value within the assumptions and cost categories considered in the study.

The cost-benefit ratio of 1.55 shows that P.P.Eye-TRACK generated approximately PHP 1.55 in measurable benefits for every PHP 1 spent. Similarly, the ROI of 55% indicates that the system produced an additional PHP 0.55 net return for every peso invested after recovering the initial cost. These estimates may be considered conservative because the main computation did not include broader cost avoidance or indirect benefits, such as the potential reduction of incident-related disruptions, improved compliance documentation, or enhanced allocation of safety personnel. Taken together, the results suggest that a CCTV-compatible, open-source, and locally deployed AI monitoring system may provide a financially accessible alternative for SMEs compared with high-cost proprietary safety platforms.

The economic feasibility of the system is further supported by the cost-benefit ratio exceeding 1.00, which means that the projected financial benefits were greater than the implementation costs under the assumptions adopted in this study. Although AI-assisted monitoring requires initial investment in hardware, software configuration, deployment, and maintenance, these costs may be offset over time by improvements in operational efficiency, reduced administrative workload, stronger safety documentation, and more effective use of safety personnel. These findings highlights that the financial value of the system should be interpreted not only in terms of direct savings but also in relation to its capacity to support more organized and proactive safety management practices.

These findings are consistent with previous occupational safety research emphasizing that preventive technologies can generate long-term organizational benefits through reductions in workplace incidents, improved productivity, and more efficient resource utilization (Leigh, 2011; Grimani et al., 2018). In the context of SMEs, the affordability demonstrated by P.P.Eye-TRACK suggests that intelligent construction safety monitoring can be positioned as a practical investment rather than an inaccessible technological innovation. Therefore, the cost-benefit results strengthen the overall argument that AI-assisted PPE monitoring can be both technically useful and economically viable when designed around existing CCTV infrastructure, local deployment, and user-oriented dashboard functions.

3.7. Pilot-to-final evaluation and overall discussion

System refinements after the pilot evaluation produced positive changes in five of the six assessment themes. Table 8 presents the mean comparison. Cost-benefit maintained the same high rating, while system performance and overall assessment showed the largest improvements.

Table 8 Statistical summary of deployment detection results

Assessment Theme	Pilot Mean	Final Mean	Mean Difference	Change
Detection accuracy	4.55	4.65	0.10	Increased
System performance	4.575	4.825	0.25	Increased
Dashboard usability	4.75	4.875	0.125	Increased
UI/UX design	4.825	4.925	0.10	Increased
Cost-benefit	4.625	4.625	0.00	No change
Overall assessment	4.5938	4.8125	0.2188	Increased

Note. Pilot and final mean scores were based on the same eight respondents who evaluated P.P.Eye-TRACK before and after system refinement. Mean difference was computed by subtracting the pilot mean from the final mean, with positive values indicating improvement after refinement. The cost-benefit theme showed no change because the pilot rating was already high and remained stable in the final evaluation.

The Wilcoxon Signed-Rank Test was applied because the same eight respondents evaluated P.P.Eye-TRACK during both the pilot and final assessment phases. The comparison demonstrated the value of iterative development, as the refinements implemented after the pilot evaluation improved respondent ratings in detection accuracy, system performance, dashboard usability, UI/UX design, and overall assessment. The unchanged cost-benefit rating should not be interpreted as a weakness, since the pilot assessment for this theme was already high and therefore left limited room for further improvement. These findings emphasize that pilot testing and user feedback are essential before full implementation, particularly for safety technologies that must operate within actual construction workflows and align with the needs of site personnel.

Beyond the survey improvements, the integration of automated PPE detection with dashboard analytics demonstrates how AI-assisted monitoring can support continuous observation, timely identification of potential PPE violations, and more systematic documentation of workplace safety activities. These capabilities strengthen data-driven decision-making by allowing safety officers to review evidence, monitor recurring issues, and respond more proactively to compliance concerns. Consequently, P.P.Eye-TRACK may be viewed as an accessible and economically viable framework for intelligent occupational safety monitoring, particularly for small and medium-sized construction firms seeking affordable digital transformation solutions that enhance, rather than replace, human safety supervision.

3.8. Practical implications

The findings indicate that P.P.Eye-TRACK can support the work of safety officers by reducing dependence on continuous manual viewing, producing structured violation records, and generating dashboard-based evidence that can guide corrective action. However, its practical value is strongest when the system is integrated into a broader safety management process rather than treated as an isolated technological solution. Effective implementation should therefore include worker orientation, camera calibration, safety officer review, field validation, documentation procedures, and management feedback. In this context, P.P.Eye-TRACK should be understood as a decision-support tool that strengthens safety monitoring practices, not as a stand-alone enforcement mechanism.

A key practical contribution of this study is the observed gap between model validation accuracy and actual deployment accuracy. Although the YOLOv8 model performed strongly under validation conditions, its field performance was influenced by several construction-site factors, including object size, visibility, lighting, obstruction, worker posture, camera perspective, and detection zone. This result offers an important caution for construction firms adopting AI-assisted safety systems: high mAP values during model validation do not automatically translate into equally high accuracy during real-world deployment. For this reason, field validation, local dataset expansion, site-specific camera calibration, and continuous performance monitoring remain necessary to ensure that AI-based PPE detection remains reliable under practical working conditions.

For SMEs, the main value of P.P.Eye-TRACK lies in its combination of affordability, dashboard usability, and practical monitoring support. By using CCTV-based deployment, local processing, and open-source AI tools, the system reduces the adoption barrier for firms that may not have the financial or technical capacity to invest in complex enterprise surveillance platforms. At the same time, affordability should be balanced with responsible implementation. Deployment should include clear privacy safeguards, transparency with workers, limited and purpose-specific data use, and human review of system-generated alerts to avoid excessive surveillance and maintain worker trust (Republic Act No. 10173, 2012; Zuboff, 2019).

4. Conclusion

P.P.Eye-TRACK demonstrated the feasibility of combining YOLOv8-based PPE detection with dashboard analytics for construction safety monitoring. The system achieved strong model-level validation performance and excellent dashboard usability, while field deployment confirmed that practical accuracy depends on PPE type, camera placement, detection zone, lighting, obstruction, and scene complexity. Hard hats and safety vests were more reliably detected than safety shoes, making lower-body PPE detection the main technical limitation of the current version.

The system met average real-time FPS and latency thresholds and produced favorable cost-benefit indicators, suggesting potential value for SME construction firms. However, implementation should not be treated as a plug-and-play installation. Companies should conduct site calibration, Green Zone/Red Zone verification, user orientation, privacy briefing, pilot testing, and human verification of alerts before full deployment. Future work should expand the safety-shoe dataset, include more construction sites, code environmental variables for formal testing, improve FPS stability, and validate long-term safety outcomes.

Overall, P.P.Eye-TRACK demonstrates that affordable artificial intelligence technologies can be successfully integrated into existing construction safety practices without replacing the expertise and professional judgment of safety officers. By combining real-time computer vision with practical dashboard analytics, the proposed system enhances PPE compliance monitoring, supports evidence-based decision-making, and contributes to safer, more efficient, and more sustainable construction workplaces. These contributions directly support United Nations Sustainable Development Goal (SDG) 8: Decent Work and Economic Growth, and SDG 9: Industry, Innovation and Infrastructure through the promotion of innovative technologies that improve occupational health, worker protection, and responsible industrial development.

Compliance with ethical standards

The study was conducted in accordance with applicable institutional research policies and ethical standards. Prior permission was obtained from the participating construction company before the conduct of the pilot deployment, data collection, and system evaluation. The research was limited to PPE compliance observation and dashboard usability assessment, and it did not involve facial recognition, biometric identification, worker identity tracking, or any form of automated disciplinary action. Participants who joined the usability evaluation provided informed consent after being briefed on the purpose of the study, the voluntary nature of their participation, the confidentiality of their responses, and their right to withdraw at any time without consequence. The authors declare that they have no known competing financial interests or personal relationships that could have influenced the conduct or reporting of this study. Data generated during the deployment are not publicly available because they include images from an active construction site and are covered by confidentiality and privacy considerations; however, aggregated findings may be made available from the corresponding author upon reasonable request and with permission from the participating organization. During manuscript preparation, Microsoft Copilot and ChatGPT were used only to assist with language refinement, grammar checking, readability improvement, and organization of written content. All AI-assisted outputs were reviewed, verified, and edited by the authors, who take full responsibility for the accuracy, integrity, originality, and scholarly quality of the manuscript.

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