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AI-ASSISTED PPE COMPLIANCE MONITORING IN MANUFACTURING: A FRAMEWORK FOR PERFORMANCE EVALUATION AND OCCUPATIONAL SAFETY INTERVENTION

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ABSTRACT
Background: Visual artificial intelligence (AI) can support the recognition of selected personal protective equipment (PPE), but its value for occupational safety depends on whether the system evaluates applicable task requirements, detects observable noncompliance, and enables a suitable response. Objective: This article develops a decision-centered framework for specifying, evaluating, and implementing AI-assisted PPE compliance monitoring in manufacturing. Methods: An integrative synthesis combines occupational safety requirements, peer-reviewed industrial and construction PPE-detection studies, object-detection evaluation methods, human–automation research, and implementation principles. Framework: Six coordinated functions are proposed: (1) task- and hazard-specific rule definition; (2) monitoring coverage and assessability; (3) worker–PPE association and violation-event construction; (4) independent performance assessment; (5) human verification and corrective intervention; and (6) governance and iterative reassessment. The framework distinguishes object-level recognition from event-level detection and operational performance, including false-alert workload, detection latency, coverage, and corrective-action follow-through. Application: Four illustrated workflows and three implementation tables translate these functions into measurable evidence requirements and decision points, using eye-protection monitoring as an example. Conclusion: The framework provides an operational specification for manufacturers to evaluate AI-assisted PPE monitoring as part of established occupational safety systems, with human accountability for compliance judgments and interventions.

Keywords:
occupational safety; personal protective equipment; eye and face protection; computer vision; artificial intelligence; manufacturing; compliance monitoring; safety intervention

1. INTRODUCTION
Manufacturing operations expose workers to flying particles, metal fragments, chemical splashes, dust, and mechanical hazards. Where risks remain following elimination, substitution, engineering, and administrative controls, personal protective equipment (PPE) constitutes an additional safeguard. In the United States, OSHA requires an appropriate hazard assessment and PPE selection under 29 CFR 1910.132, with requirements for eye and face protection specified in 29 CFR 1910.133 [1,2]. Effective monitoring therefore begins with the work activity and required protection, not merely the visual presence of an item. The hierarchy of controls and safety-management processes establish the operational context in which monitoring results should be interpreted [3,4]. The ILO's recognition of a safe and healthy working environment as a fundamental principle and right at work reinforces the importance of preventive systems [5].
Computer vision has been applied to PPE detection in learning-factory and industrial environments, including protective eyewear and other industrial equipment categories [6–8]. Related work in construction has evaluated hardhats, fall-protection harnesses, PPE recognition, and worker-specific monitoring across cameras [9–13]. These technical advances make automated observation feasible for selected visual tasks, while leaving practical questions for EHS professionals: Which equipment is required in a particular task? What counts as an independent violation episode? How often is a relevant area actually assessable? Which notifications require immediate action? And how should performance be interpreted when alerts cannot establish fit, equipment ratings, or full hazard control?
A detection metric alone answers only part of these questions. A system may identify a pair of glasses yet be unable to determine their approved protective specification; an alert may be technically correct yet arrive too late for useful intervention; or a camera may operate continuously while the relevant workstation is obscured. These distinctions motivate a structured link between the detector, operational oversight, and corrective action.

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The objective of this article is to develop an auditable methodological framework addressing three questions: (RQ1) How should task-specific PPE requirements and observable compliance opportunities be defined? (RQ2) Which technical and operational endpoints provide a meaningful assessment of AI-assisted monitoring? (RQ3) How should candidate alerts be translated into accountable occupational safety interventions? The contribution is a practical evaluation architecture that connects independent evidence of detectable events to decisions made within an EHS management system.

2. METHODOLOGICAL APPROACH AND EVIDENCE SYNTHESIS

An integrative methodological synthesis was used to connect concepts and evaluation practices that are often discussed separately in occupational safety management, computer vision, and human factors. This approach is suited to organizing complementary literatures into a testable framework, rather than estimating a pooled effect [15]. The analysis considered five evidence domains: occupational PPE obligations and safety-management guidance [1–5,14]; industrial and construction PPE detection [6–13,16,17]; model evaluation and annotation [20,21,23]; human oversight, trust, and acceptance [24–28]; and implementation and governance [22,29–33].

Framework construction proceeded in four stages. First, applicable PPE requirements were translated into worker–task–zone opportunities for observation. Second, the evaluation units were distinguished as visible objects, worker-specific status, violation episodes, and actionable alerts. Third, the technical outcomes were connected to operational denominators and work processes. Fourth, the framework was closed with accountable verification, corrective action, and reassessment. Existing sensing and smart-PPE models informed the system perspective [16,17], while application to manufacturing tasks informed the proposed evidence requirements.

The article reports a methodological specification and illustrative operating scenarios. The figures represent conceptual workflows, and the numerical definitions describe endpoints for future evaluations. The article does not assign measured detector performance or injury-reduction estimates to the proposed system.

3. CONCEPTUAL FOUNDATION: FROM MONITORING TO INTERVENTION

3.1. Distinguish presence, wearing status, and protection adequacy

AI-based visual classification can identify that an item resembling PPE is present, while person–item association can indicate that it appears to be worn by an individual [7,8,11,13]. Neither outcome, on its own, establishes that the equipment is appropriate for a particular exposure. Eye protection illustrates the difference: recognition of eyewear cannot reliably certify lens impact rating, peripheral protection, or the suitability of the device for the identified hazard. Likewise, visible placement does not demonstrate respirator fit testing or compliance with every element of a respiratory protection program.

The framework defines an observable compliance opportunity as the intersection of a worker, a specific task or authorized zone, an applicable PPE rule, and a period in which the required wearing status can be assessed. Where the rule or the image is insufficient to establish that status, the assessment remains indeterminate. This distinction is essential to prevent workers in non-applicable areas from being classified as noncompliant.

3.2. Integrate conventional observation and automated monitoring

Manual inspection, supervisor observation, and incident follow-up contribute contextual evidence that can be complemented by automated, time-stamped visual observations. Both pathways converge at professional verification and appropriate intervention. The resulting records can support training, safety-program review, and adjustment of rules or monitoring arrangements. Figure 1 presents this integrated workflow, including the feedback connection between intervention outcomes and continuous improvement [3,14].

4. SIX-FUNCTION FRAMEWORK FOR AI-ASSISTED PPE COMPLIANCE MONITORING

4.1. Define task-specific PPE requirements

The first function is an approved PPE rule matrix. Each monitoring rule should identify the task, equipment specification, relevant area or zone, authorized exceptions, and visible criteria that can reasonably be assessed by a camera. The matrix links the rule to the organization's hazard assessment and provides a reference for judging eligibility and apparent noncompliance. For a machining operation, this may involve an eye-protection requirement during active exposure to flying chips; the presence of a person in an adjacent break area would not create the same monitoring opportunity [1,2].

4.2. Quantify monitoring coverage and assessability

The second function specifies the observational denominator. Calendar time, camera uptime, eligible task time, and assessable monitoring time are different measures. Recording duration should be documented by task, PPE category, camera view, production shift, illumination, and reasons for lost or indeterminate coverage. A monitoring program should report both the periods that can be evaluated and the periods for which the system

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makes no judgment. An unchanged image across consecutive frames should not be counted as thousands of independent worker violations.

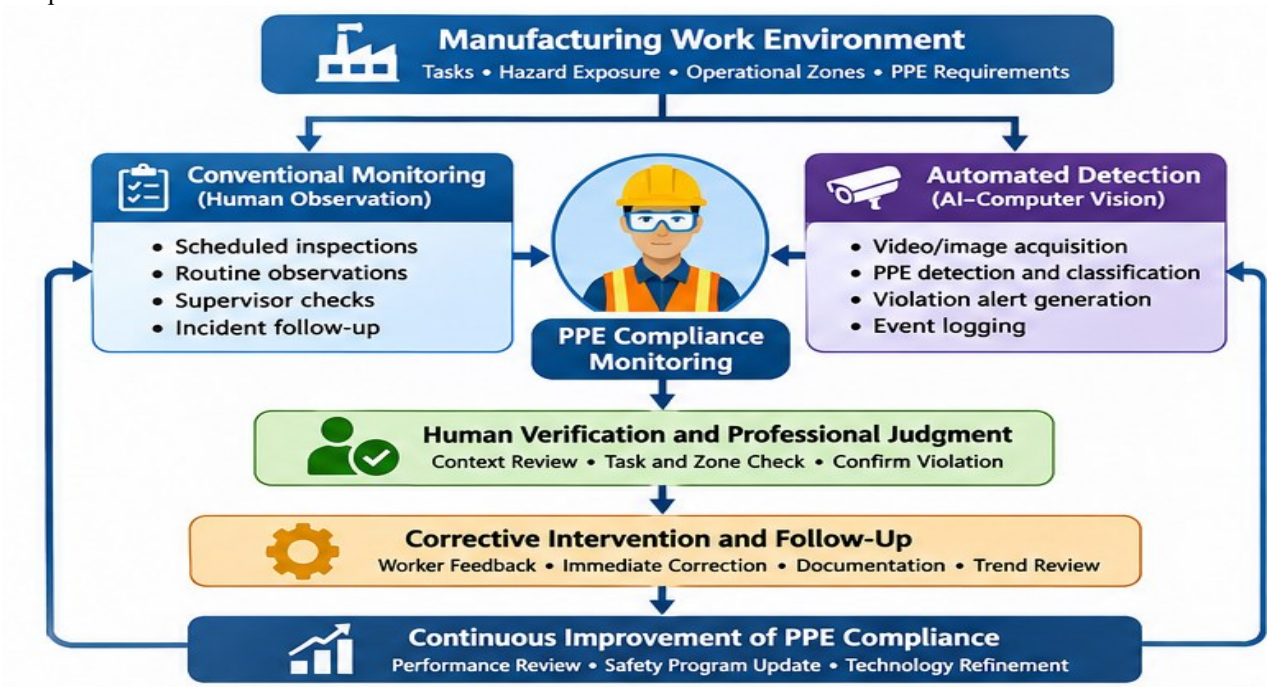


Figure 1. Conceptual framework for PPE compliance monitoring in manufacturing. Conventional observation and AI-assisted detection feed professional verification, corrective intervention, and continuous improvement; schematic illustration.

4.3. Construct worker-specific violation episodes and alerts

The third function comprises image acquisition, preprocessing, person and PPE detection, association between a worker and equipment, task-rule evaluation, and temporal consolidation of detected deviations. The design recognizes compliant, observable violation, indeterminate, and outside-scope states. Alerts are constructed from time-bounded violation episodes and are subject to deduplication and assignment to a responsible reviewer. As Figure 2 illustrates, the output of a detector becomes an EHS notification only after its PPE status is interpreted against the relevant task requirement [11,13].

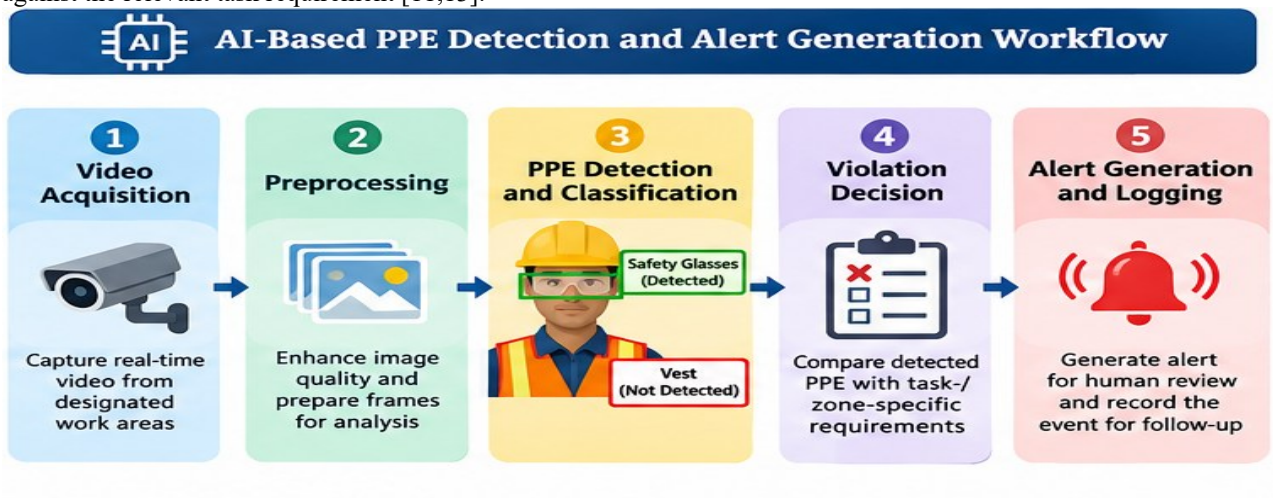


Figure 2. AI-based PPE detection and alert-generation workflow. The depicted eyewear and vest labels illustrate model outputs and task-rule checks; they are not empirical detection results.

4.4. Evaluate technical reliability and operational workability

The fourth function specifies independent ground truth, model locking, event matching, and reporting of detection quality and workload. Training, tuning, and final testing should use separated recording sessions; withholding an

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entire camera or facility for external evaluation is preferable when the data permit. The test protocol defines event duration, matching tolerances, false-alert accounting, and relevant monitoring exposure before thresholds are selected. Reporting includes missed reference events, false alerts, time to notification, and stratified performance under different working conditions [20,21].

4.5. Verify alerts and document corrective action

The fifth function connects detection to EHS practice. The routed notification identifies the applicable task rule, monitoring zone, time, relevant image or recording, and any uncertainty. An authorized reviewer confirms whether the event is actionable and records the response. Appropriate interventions include immediate hazard control, PPE replacement, employee coaching, assessment of training or supervision, and correction of equipment availability or work design. An algorithmic alert is a trigger for professional review rather than an autonomous determination of misconduct. Verification and closure times should be measured as part of program effectiveness [3,14].

4.6. Govern and periodically reassess the system

The sixth function specifies lawful purposes, access permissions, retention schedules, consultation and communication with workers, escalation criteria, and periodic technical review. Changes in PPE appearance, camera location, lighting, production conditions, and work practices should trigger reassessment. The NIST AI Risk Management Framework provides a structured approach to mapping, measuring, managing, and governing technology risk [22]. Together, these functions create a closed-loop monitoring program rather than a stand-alone image classifier.

Table 1. Six-function framework and minimum evidence required for an operational pilot.

Function	Minimum evidence	Decision supported
1. Task and PPE rules	Approved hazard/task/zone matrix; PPE specification; exceptions	Is the worker subject to an observable PPE rule?
2. Monitoring coverage	Eligible task time; camera uptime; assessable time; abstentions	How much relevant work can the system actually assess?
3. Violation-event construction	Worker–PPE association; reference episode boundaries; alert deduplication	Does an alert concern the correct person and task?
4. Independent evaluation	Locked test data; event confusion matrix; workload and latency	Is the monitoring process sufficiently dependable?
5. Human intervention	Alert acknowledgment; verification; action and closure records	Did the notification result in a suitable safety response?
6. Governance and review	Purpose controls; access, retention, audit and reassessment triggers	Can the system operate responsibly over time?

5. PERFORMANCE EVALUATION PROTOCOL

5.1. Establish an independent reference set

For each eligible worker–PPE opportunity, reviewers should classify observable compliance, observable violation, indeterminate, or outside scope using a predefined annotation guide. Where feasible, two reviewers independently label an overlapping sample before disagreements are reconciled. Agreement statistics, including raw concordance and Cohen's kappa, are interpreted alongside category prevalence [23]. The ground-truth procedure records the worker, applicable rule, onset and end of a violation episode, and relevant uncertainty. Model outputs should not be presented to annotators during initial labeling.

5.2. Report object and event performance separately

Object-level assessment uses standard localization/classification measures, such as precision, recall, average precision (AP), and mean average precision (mAP), with the intersection-over-union rule and aggregation method explicitly defined [20]. These measures are useful for comparing object recognition but are not equivalent to safety interventions. Event-level true positives (TP) are alerts matched once to independent reference violation episodes; false positives (FP) are unmatched actionable notifications; false negatives (FN) are missed reference events. Precision = TP/(TP+FP), recall = TP/(TP+FN), and a recall-weighted F_2 score = 5PR/(4P+R).

Because violations may be less frequent than compliant work, precision–recall analysis is useful for interpreting the selected alert threshold [21]. Operational reporting must also state the false-alert workload as unmatched notification episodes per assessable camera-hour, the time from event onset to alert delivery, the rate of duplicate

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alerts, the share of relevant activity not assessable, and the time to corrective action. If competing systems use different coverage denominators, their assessable fractions must be reported alongside performance rates. Confidence intervals should account for dependence between observations within recording sessions.
Figure 3 shows the proposed progression from independent test-data preparation through detector evaluation, performance measurement, and translation into an operational decision. It illustrates assessment methodology and contains no observed experimental outcomes.

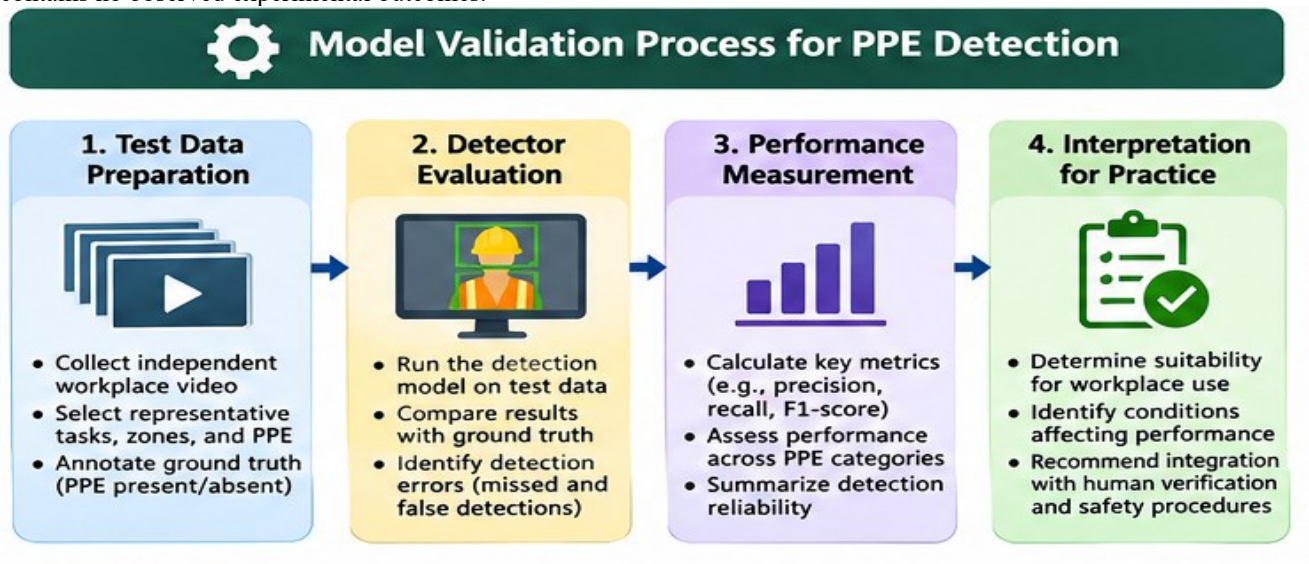


Figure 3. Proposed validation sequence for AI-based PPE detection, from independent test data to measurement and interpretation for EHS practice. Schematic procedure, not reported trial results.

Table 2. Core evaluation endpoints and their EHS interpretation.

Endpoint	Definition / denominator	Operational interpretation
Event recall	TP / (TP + FN), among independently annotated reference episodes	Share of assessable violations that generate valid alerts
Event precision	TP / (TP + FP), using one-to-one episode matching	Share of actionable alerts that refer to reference violations
False-alert workload	Unmatched alert episodes / assessable camera-hours	Demand placed on supervisors for unnecessary verification
Alert latency	Median and 95th-percentile time from onset to delivered alert	Timeliness among detected episodes; missed events reported separately
Assessment coverage	Assessable eligible task time / eligible monitored task time	How much relevant activity contributes to performance estimates
Human response	Verified actions / verified actionable alerts; time to closure	Follow-through from recognition to intervention
Robustness	Stratified performance by PPE type, shift, camera and visibility	Operating conditions requiring adjustments or additional review

5.3. Compare with conventional monitoring under equivalent conditions

The comparison between automated and conventional observation should distinguish coverage from detection sensitivity. When feasible, each approach is evaluated against the same independently coded exposure windows, tasks, and workers. Separate analyses can assess the broader observation coverage delivered by continuous monitoring compared with periodic inspections. Controlled, hazard-free demonstrations can explore difficult visual scenarios, but they should not be combined with routine footage to estimate actual noncompliance prevalence. Evidence from an unseen facility would provide stronger assessment of transferability than repeated frames from a single camera.

6. TRANSLATION INTO AN OCCUPATIONAL SAFETY INTERVENTION PROGRAM

6.1. Eye and face protection as an application case

Eye and face hazards provide a clear example of task-sensitive monitoring. A milling or grinding activity may require approved protective eyewear, while nearby tasks may involve different exposure conditions or additional face protection. OSHA's general-industry requirements under 29 CFR 1910.133 determine applicable eye and

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face protection obligations for manufacturing [2]. A separate national enforcement signal is the inclusion of construction eye-and-face protection, 29 CFR 1926.102, among OSHA's preliminary FY2022 most frequently cited standards; that construction ranking should not be interpreted as a manufacturing violation rate [34].
In a defined machining zone, a detection model may indicate that eyewear is not visible on a worker performing a task for which eye protection is required. A verified alert can prompt corrective action or supervisor contact. Where equipment is visible, the system may still need a competent person to confirm specification, condition, or fit. This scenario exemplifies how observable deviations, uncertainty, and professional review should be handled within a single monitoring rule.

6.2. Design a staged, risk-informed pilot

A structured pilot links initial hazard and rule review to representative recording, independent annotation, locked evaluation, supervised activation, and ongoing review. Thresholds for event recall, false-alert workload, and response latency should be set according to site risks and staffing capacity. Organizations can also document whether timely, verified notifications produce completed corrections or improvements in work practices. Figure 4 displays the resulting six-function feedback cycle, in which monitoring evidence and corrective-action experience inform subsequent configuration and governance decisions.

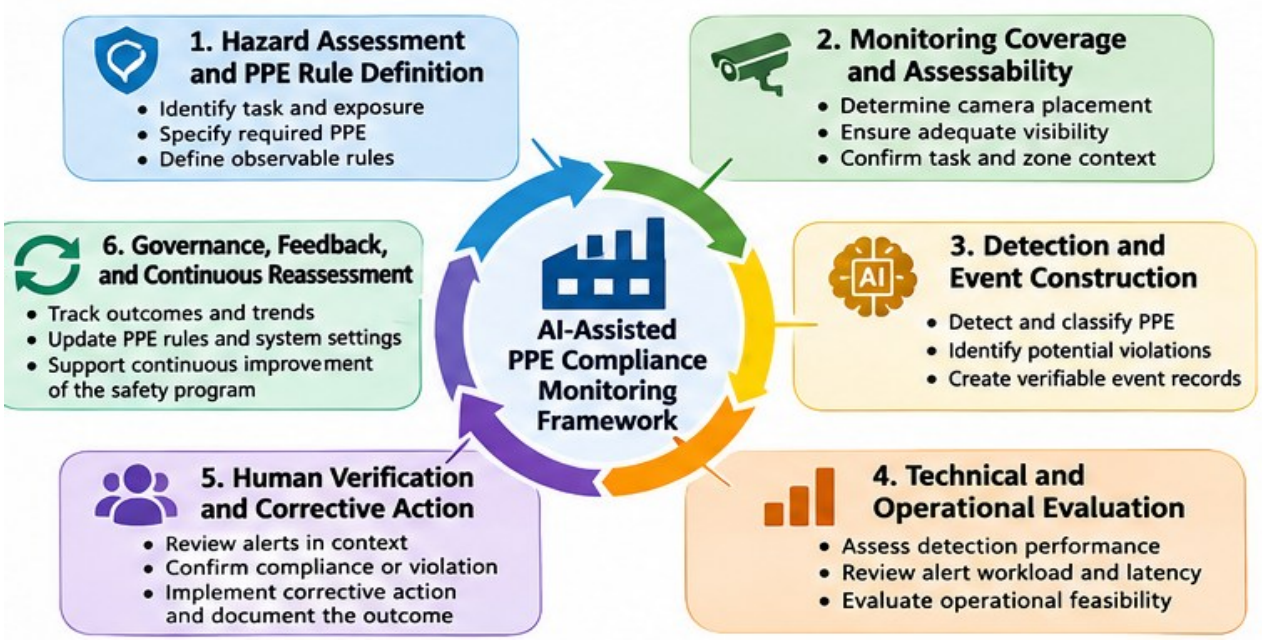


Figure 4. Integrated deployment and continuous-improvement cycle for AI-assisted PPE monitoring. Six proposed functions link hazard rules, visibility, detection, evaluation, corrective action, and governance.

Table 3. Proposed stages, decision gates and reporting outputs for workplace implementation.

Stage	Required activity	Minimum report / decision
Specification	Hazard assessment, scope, PPE rule mapping, privacy and role review	Approved use case and predefined acceptance criteria
Silent evaluation	Representative observations, label protocol and baseline workflow	Dataset inventory, coverage map and annotation agreement
Locked test	One-to-one event matching, object and event metrics, robustness tests	Detection, workload, coverage and latency with uncertainty
Supervised activation	Reviewer verification, routing, worker feedback, action logging	Verification burden, response times and resolved events
Periodic reassessment	Review equipment, task, staffing and camera changes	Continued-use decision and improvement priorities

6.3. Measure adoption and organizational performance

A successful pilot depends on EHS professionals, operations supervisors, and workers being able to interpret and use alerts. Research on the appropriate reliance on automation, task allocation, and technology acceptance

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emphasizes trust, perceived usefulness, ease of use, and supporting conditions [24–28]. Relevant outcomes include supervisor time per verified episode, training demand, employee feedback, disputed notifications, correction time, system maintenance burden, and integration with established inspection and reporting channels. Implementation science distinguishes feasibility and adoption from fidelity, costs, reach, and sustainability [32,33]; those constructs can be translated into workplace-specific indicators.

7. RESPONSIBLE USE, PRIVACY, AND REGULATORY ALIGNMENT

Visual monitoring may collect identifiable information and generate inferences about worker behavior. Implementation planning should therefore define the safety purpose, minimum data required, permitted recipients, retention and deletion schedule, mechanisms for challenging incorrect alerts, and safeguards against inappropriate secondary use. European occupational-safety work on smart monitoring recognizes the opportunities and organizational challenges of these technologies [29]. Where relevant, the European Union General Data Protection Regulation requires a context-specific assessment of lawful processing, transparency, and data minimization [30]. System validation should consider differences in lighting, camera perspective, PPE appearance, worker density, and work activity. Performance review can identify operating conditions that increase indeterminate assessments or errors without making unsupported personal or demographic inferences. Identity tracking across multiple cameras should be justified by the monitoring purpose; the availability of a capability does not itself establish that a workplace needs it [13,22].

Technical system performance and regulatory compliance occupy different levels of assessment. OSHA PPE duties remain tied to hazard identification, selection, and use [1,2]; ISO 45001:2018 provides the broader occupational health and safety management-system framework [4]. Great Britain's Personal Protective Equipment at Work Regulations and supporting HSE guidance establish obligations within their own jurisdiction [31]. A camera can support verification of selected visible behaviors but does not certify an entire PPE program or independently establish legal conformity.

8. DISCUSSION

The proposed framework makes a practical distinction between recognizing an object and delivering dependable occupational safety information. It links the applicable task rule to the observation, converts repeated frames into independently defined events, requires transparent exposure denominators, and then evaluates whether a verified alert generates an appropriate response. This structure places AI-assisted PPE monitoring within established EHS roles rather than treating the detector as a stand-alone compliance authority.

Three advances follow from this synthesis. First, the framework makes rule applicability explicit, addressing the problem that a PPE item may be present or absent without that visual state indicating a violation. Second, it makes model assessment more relevant to operational work by incorporating missed events, false-alert burden, latency, and assessable coverage alongside common recognition metrics. Third, it connects technical evaluation with organizational implementation through human verification, worker communication, corrective-action closure, and periodic reassessment. These linked functions provide a common basis for evaluation across PPE categories and industrial settings.

A practical strength is the framework's applicability to different detection architectures and manufacturing environments. Sites can define the PPE classes and monitoring purposes most relevant to their hazards while maintaining consistent evaluation definitions. The model is also compatible with conventional inspections and other safeguards: AI-assisted monitoring can provide additional observations without displacing hazard elimination, effective engineering controls, appropriate PPE selection, or competent supervision.

Application requires site-specific calibration because risk, visibility, task variability, and staffing differ across manufacturing facilities. A visually assessable rule for safety glasses may not be transferable to protection attributes that require physical examination or supporting records. Furthermore, the framework identifies how monitoring and intervention should be evaluated; evidence of lasting changes in compliance behavior or occupational injuries requires prospective studies with suitable comparison conditions and follow-up. These research priorities provide defined endpoints for future validation.

9. CONCLUSION

AI-assisted PPE compliance monitoring can be integrated into manufacturing EHS systems through a coordinated sequence of hazard-based rule definition, assessment of monitoring coverage, worker-specific violation-event construction, independent technical evaluation, human verification and corrective action, and ongoing governance. The four illustrated workflows and operational evaluation tables specify the evidence needed to move from visual observations to responsible intervention decisions. This decision-centered framework provides a

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structured basis for selecting, evaluating, and improving automated PPE monitoring as a complement to professional judgment and established occupational safety controls.

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