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A Data-Driven Lean Continuous-Improvement Training System Using Markerless Motion Capture for Built-Environment Work: A Quasi-Experimental Field Evaluation

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Abstract

Newly hired workers in construction, industrialized building production, and other built-environment operations often face elevated safety and ergonomic risk while learning manual tasks. At the same time, many onboarding programs still rely on observation, verbal coaching, and checklist-based sign-off, which can be difficult to standardize across supervisors and sites. This study presents the development and field evaluation of a data-driven training system that integrates markerless motion capture, machine-learning-assisted ergonomic risk scoring, and Lean/continuous-improvement (CI) routines to provide structured coaching during onboarding. A single-site, non-randomized quasi-experimental sequential-cohort design compared a traditional onboarding cohort with a subsequent app-supported cohort (n = 20 each). Primary outcomes were time to qualification, training cost, and task accuracy. Secondary site-level indicators were safety compliance and musculoskeletal (MSK) injury outcomes. Compared with the traditional cohort, the app-supported cohort reached qualification sooner (5.85 ± 1.50 vs. 18.60 ± 3.50 calendar months), at lower cost (SR 29,250 ± 7602 vs. SR 93,000 ± 17,348 per employee), and with higher task accuracy (88.60 ± 5.70% vs. 60.65 ± 10.60%). Welch's t-tests showed statistically significant differences across all primary outcomes (all $p < 0.001$), although the standardized effect sizes were very large and should be interpreted cautiously given the modest sample and non-randomized design. Safety compliance (+68%) and MSK injuries (−25%) are reported only as descriptive site-level indicators because denominator and exposure data were not available for inferential analysis. The study contributes a practical intervention model linking ergonomic sensing to coaching cues, auditable training logs, A3 problem solving, and standard work refinement. The findings suggest that this integrated approach is promising for built-environment onboarding, but multi-site studies with stronger comparative designs, individual-level reporting, and fuller algorithmic documentation are needed.

Keywords: construction safety; occupational safety and health; training evaluation; markerless motion capture; lean; continuous improvement; standard work

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1. Introduction

Built-environment industries continue to face persistent challenges related to worker safety, onboarding efficiency, and consistency of task execution. Newly hired workers are particularly vulnerable because they must learn unfamiliar tasks, local procedures, and safe movement patterns while operating under production pressure. Traditional onboarding commonly depends on supervisor observation, verbal correction, and paper checklists, which may vary across trainers and provide limited objective evidence regarding movement quality or ergonomic exposure [1,2].

Lean and continuous-improvement (CI) approaches have been used to stabilize work, standardize operations, reduce waste, and improve safety performance when safety is treated as an integral performance dimension rather than as a separate compliance activity [3–6]. However, Lean-oriented onboarding still often depends on episodic observation, paper checklists, and supervisor judgment. These methods are useful, but they provide limited high-frequency evidence about posture, movement quality, or ergonomic exposure during skill acquisition.

In parallel, digital safety technologies such as computer vision, AI-assisted monitoring, sensor-based monitoring, explainable alerts, immersive training, XR-based learning systems and markerless motion capture have matured rapidly [7–20]. Markerless systems can estimate posture without wearable markers, while learning-based methods can support classification of manual material handling tasks and risk-relevant movement patterns [11,12]. Yet many published systems remain point solutions. They detect a hazard, classify a posture, or visualize a risk, but they are not tightly integrated into structured coaching, standard work updates, or formal CI routines.

Although markerless motion capture and machine-learning approaches have shown promise for ergonomic assessment, many prior studies examine these tools as standalone technical systems. Far less attention has been given to how ergonomic sensing can be embedded into real onboarding workflows, supervisory coaching routines, and Lean/continuous-improvement practices in live built-environment operations. Therefore, the objective of this study was to develop and evaluate a closed-loop onboarding intervention that integrates markerless motion capture, ergonomic risk scoring, coaching prompts, auditable training records, and continuous-improvement follow-up actions. Recent studies further emphasize the need to integrate ergonomic sensing with supervisory workflows and operational continuous-improvement systems rather than treating these technologies as isolated analytical tools [21–29].

The contribution of this paper is not a standalone machine-learning benchmark. Instead, it is a practical field-deployed intervention demonstrating how ergonomic sensing can be translated into structured coaching routines, standardized onboarding, A3 problem solving, and measurable operational outcomes.

Despite progress in digital safety technologies and ergonomic sensing, relatively few studies have examined how such tools can be embedded into real onboarding systems that include supervisor coaching, standardized work updates, auditable training records, and continuous-improvement routines. This implementation gap is particularly relevant in built-environment operations where new workers must rapidly achieve safe and reliable performance under variable site conditions. Accordingly, this study evaluates an applied intervention rather than a standalone algorithm benchmark.

1.1. Research Question and Hypothesis

- Q1: Is the app-supported onboarding approach associated with shorter time to qualification and lower training cost than the traditional onboarding approach?
- Q2: Is the app-supported onboarding approach associated with higher task accuracy during qualification?
- Q3: How do site-level safety indicators and implementation features align with the proposed closed-loop coaching mechanism?

H1. *The app-supported cohort will show lower time to qualification and lower training cost than the traditional cohort.*

H2. *The app-supported cohort will show higher task accuracy than the traditional cohort.*

H3. *Safety compliance and MSK injury indicators are treated as exploratory site-level outcomes because only aggregate percentage summaries were available.*

1.2. Novelty and Contribution

The novelty of this work is not markerless motion capture alone, but a replicable intervention that translates pose-derived ergonomic risk into standardized coaching actions and embeds those actions into continuous-improvement routines. The study contributes the following:

- Provides a clearer and more defensible description of an integrated intervention that combines markerless motion capture, ergonomic scoring, and Lean/CI routines.
- Reports field outcomes using a quasi-experimental sequential-cohort design with transparent independent-group statistics for the primary outcomes.
- Clarifies the practical mechanism by which pose-derived risk signals were converted into coaching prompts, standard work revisions, and A3 follow-up actions while preserving worker privacy through posture-feature retention rather than routine raw video storage.

Lean/CI systematically surfaces waste and safety gaps; motion capture provides objective kinematic signals for ergonomic risk; and ML enables real-time inference and individualized feedback. This integration approach aligns with recent research trends in intelligent safety systems and adaptive training environments [18–20,23–28]. Together, these elements are well-suited for safety-critical training, where timely, objective guidance can accelerate learning, standardize performance, and reduce incidents. This aligns with performance-based learning approaches that tie training to actual behavior and outcomes [2,3].

2. Related Work

Prior studies have shown that onboarding quality significantly influences worker safety, productivity, and skill transfer. Structured training, repetition, immediate feedback, and supervisor consistency are associated with better learning outcomes [3–6]. Empirical and conceptual studies have linked Lean practices to safer workflows, better supervision, and more structured safety planning, although the strength of this evidence varies by experiment and study design [3–6]. The training literature similarly emphasizes that safety training is more effective when it is task-specific, behavior-linked, and supported by feedback rather than delivered as a one-time compliance exercise [1,2,16,17].

Given this landscape, the present work positions a closed-loop training intervention that (i) measures kinematic risk during training sessions, (ii) converts risk signals into standardized coaching actions, and (iii) logs and feeds these actions into CI artifacts (standard work updates, A3 problem solving). This combination is intended to clarify the mechanism of change and improve implementation fidelity in real work settings. In this section, a contrast between the proposed approach with representative state-of-the-art studies is presented to clarify methodological differences and practical gains. Tables 1 and 2 summarize the key differences between representative prior work and the present study in terms of methods, outcomes, and deployment scope.

Table 1. Comparative analysis versus representative prior work.

Criteria	Representative Prior Work	This Work
Methodology	Traditional Lean or isolated digital tools (e.g., AHP routines, VR scenarios, PPE monitoring)	Integrated Lean Six Sigma + motion capture + ML with CI loops
Ergonomic risk	Manual/periodic checks or standalone classifiers	Real-time ergonomic scoring driving training feedback
Training efficiency	Limited measurement of learning curves	Quantified reductions in time and cost with inference tests
Safety outcomes	Moderate gains	Substantial gains (+68% compliance; −68.5% time/cost; +46.1% accuracy)
Statistical design	Often descriptive	Welch/Student *t*-tests, effect sizes, 95% CIs
Deployment scope	Point solutions	Unified tool for high-risk settings

Table 2. How the present study extends representative prior work.

Literature Stream	What is Commonly Reported	Remaining Gap	How This Study Responds
Lean/CI and construction safety	Lean practices can improve workflow reliability and may support safety through standardization, supervisory routines, education, and management alignment; recent review and buildings evidence also stress managerial perception and accountability [3–6,30–33].	Many Lean and management studies still treat training or safety implementation broadly and do not show how real-time ergonomic evidence is translated into day-to-day coaching during onboarding.	The intervention links detected ergonomic risk to standardized coaching cues, A3 follow-up, and standard work updates during onboarding.
Digital safety technologies	Computer vision, sensing, immersive learning, and XR-based safety systems are growing quickly, but recent framework work shows they often remain fragmented from broader workflows unless tied to BIM, Lean, and formal safety management [18–29,34].	Many systems remain point solutions that are not embedded in supervisory routines, training governance, or CI cycles.	The app is framed as a supervisory decision-support tool rather than as an isolated technology benchmark.
Markerless motion capture and ergonomics	Markerless motion capture can estimate posture and support ergonomic assessment; adjacent eye-tracking work shows training and experience also reshape visual hazard recognition behavior [11–15,27,28,35].	Technical studies rarely report onboarding outcomes such as qualification time, training cost, or how sensed risk is translated into coaching.	The field evaluation focuses on onboarding outcomes while preserving a conservative non-benchmark framing of the ML component.
Construction safety training	Construction safety training is strongest when it is task-based, feedback-rich, reinforced over time, and increasingly differentiated by transfer demand, multilingual-workforce context, and worker profile [1,2,16,18–20,33,36–41].	Most studies stop at classroom, lab, simulation, or content-generation settings and rarely evaluate live onboarding workflows linked to ergonomic sensing and Lean artifacts.	The study tests that integration under live operating conditions using a sequential-cohort field design.

Table 2. *Cont.*

Literature Stream	What is Commonly Reported	Remaining Gap	How This Study Responds
Lean-enhanced immersive training	Recent buildings evidence shows that immersive VR can improve hazard recognition and, in some cases, productivity and ergonomic safety when paired with structured feedback or Lean concepts [39,40,42].	The strongest published examples still center on simulation or laboratory-style training rather than live field onboarding and supervisory CI routines.	The present study examines live onboarding, markerless motion capture, and standard work-linked coaching in operational conditions.
Safety–productivity linkage	Recent buildings evidence frames safety compliance and human factors as mechanisms that connect training, management practice, and operational productivity [31–33].	These models clarify the safety–productivity relationship but do not examine ergonomic feedback during onboarding.	The present study treats safety and onboarding efficiency as linked outcomes, while remaining cautious about causal claims.

The literature review and the gap analysis methodology are shown in Figure 1. Also, Figure 2 illustrates the literature review mechanism and gap analysis process that guided the design of the proposed application.

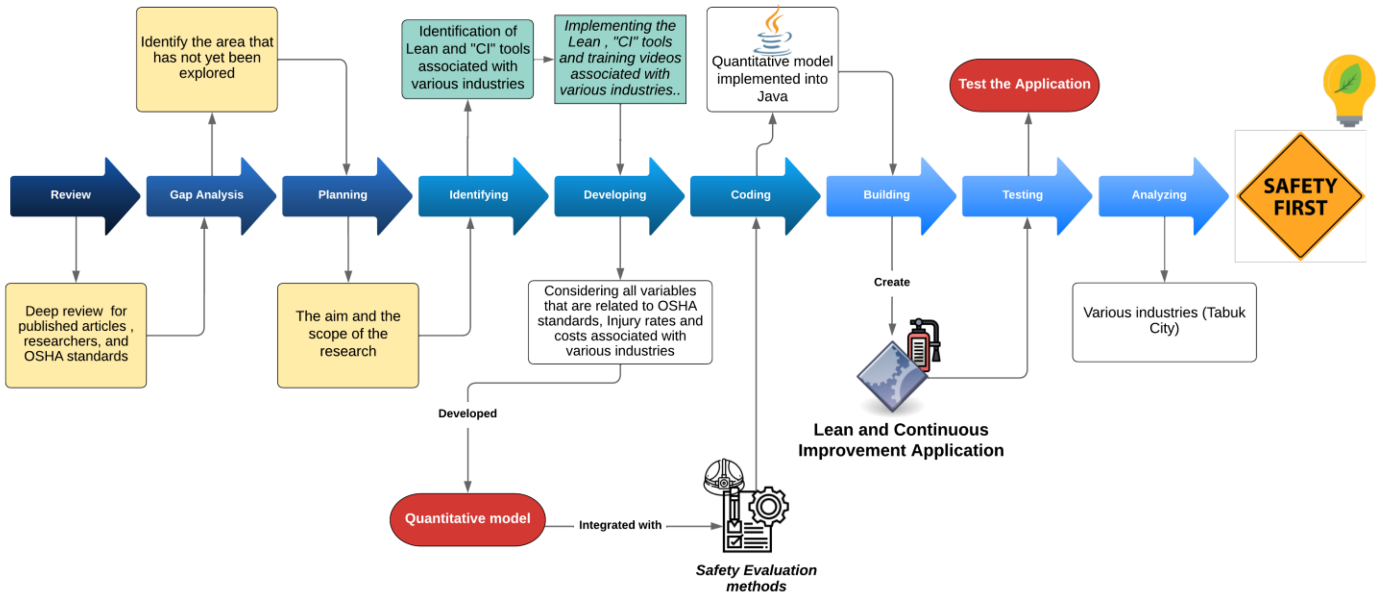

Figure 1. Research methodology.

2.1. Lean/CI and Safety: From Efficiency to Risk Reduction

Lean management and continuous-improvement (CI) approaches have been widely associated with improved efficiency, waste reduction, process standardization, and safer work practices in high-risk industries, including construction and built-environment operations [3,4,9,23,43]. Tools such as standard work, visual management, root-cause analysis, and A3 problem solving can support more consistent onboarding and faster learning cycles. However, many existing applications still rely heavily on manual observation and retrospective reporting, with limited integration of objective ergonomic data during training. This gap highlights the opportunity to combine Lean/CI routines with real-time movement analytics to strengthen coaching quality, training consistency, and continuous operational learning [8,16].

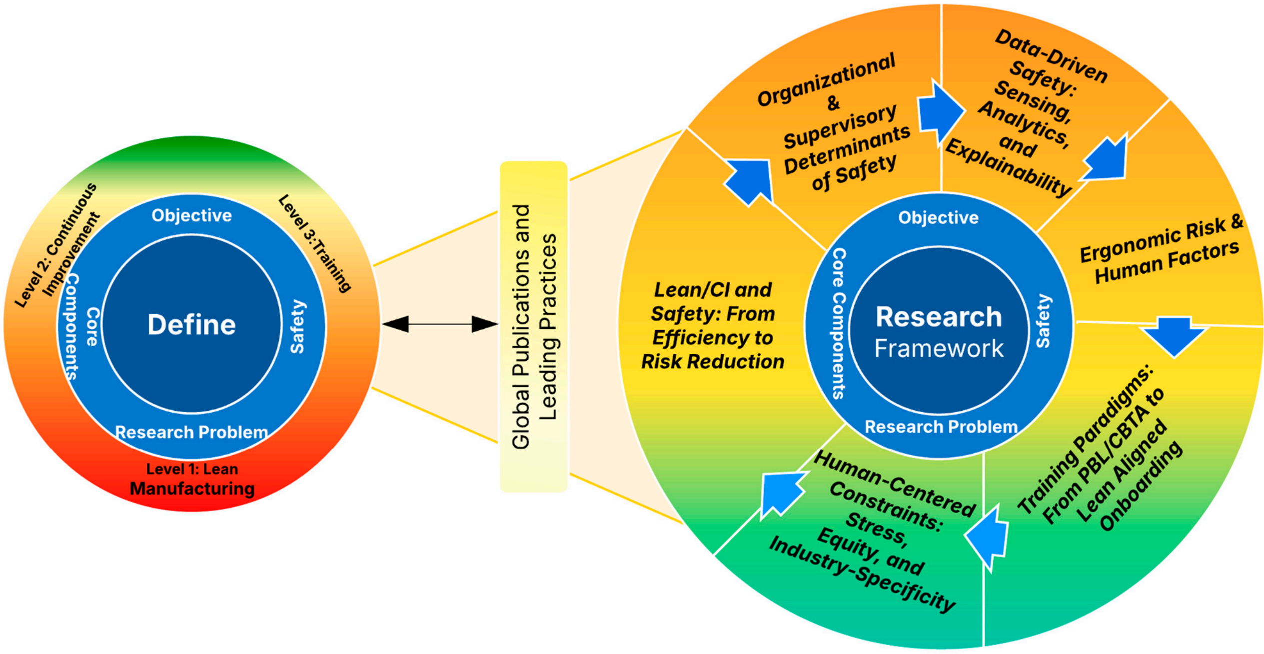

Figure 2. The review mechanism.

2.2. Digital Ergonomics, Motion Capture, and Workplace Feedback

Workplace safety research increasingly uses sensing and analytics to identify hazards, improve compliance, and strengthen learning. Recent studies describe AI- and sensor-based workplace safety management, personal protective equipment monitoring, explainable visual detection, XR-assisted learning environments and immersive simulation approaches [7–20]. Construction-specific reviews also document rapid growth in computer vision methods for monitoring unsafe acts, work-related behaviors, and site interactions, while noting persistent challenges related to occlusion, generalization, and operational deployment [21,22]. In ergonomics, markerless motion capture and motion-analysis systems can estimate posture, support ergonomic assessment, and classify manual tasks with promising accuracy under controlled or semi-controlled conditions [11–15]. These technologies are valuable because they reduce dependence on subjective observation and enable higher-frequency measurement of physical exposure during work and training.

Even so, two limitations are common in the literature. First, many digital safety systems focus on detection rather than behavior change; they identify a risk but do not specify how supervisors should respond in a standardized way. Second, many motion capture and machine-learning studies emphasize technical performance but do not report how the resulting signals are embedded in operational routines such as coaching, standard work, or CI follow-up [11–15,21,22]. For built-environment onboarding, this translation gap matters because improvement depends not only on sensing posture but also on converting sensed risk into timely and actionable guidance.

2.3. Construction Safety Training Effectiveness and Immersive Learning

The evidence base on construction safety training has also become more rigorous. A systematic review of traditional and computer-aided health-and-safety training in construction found that both conventional and digital methods can improve learning and behavior, but emphasized the need for clearer outcome reporting, usability reporting, and stronger evaluation designs [44]. Subsequent reviews of immersive technologies across the construction sector show that VR/AR and related systems can enhance engagement, hazard communication, and experiential learning, but the effectiveness of these tools depends heavily on realism, usability, and alignment with the work context [45–47].

More focused construction studies reinforce that point. Training transfer in VR settings has been linked to telepresence, risk perception, and trainee satisfaction [48], while interactive design features such as immediate feedback and object interaction can improve individual learning performance [49]. Other recent work shows that VR-based training can outperform traditional methods for hazard identification in some settings, yet outcomes vary across learning styles and site conditions [46,50]. Meta-analytic and field evidence further indicates that safety behavior is shaped by supervision, motivation, safety climate, and contextual fit rather than by training delivery mode alone [43,51]. Together, these findings support personalized, feedback-rich training but caution against treating technology as a substitute for supervisory practice and organizational routines.

2.4. Synthesis, Gap, and Positioning of the Present Work

Most previous work focuses either on sensing technologies or management routines. This study examines their practical integration through a closed-loop onboarding intervention. The present study is positioned at the intersection of Lean/CI, construction safety training, and digital ergonomics. Rather than evaluating a standalone computer vision benchmark, it examines a field intervention in which markerless motion capture supports a coaching and improvement workflow. The study therefore complements technical ergonomics research by asking whether the integration of sensing, feedback, and CI routines is associated with meaningful onboarding outcomes under live operating conditions. It responds directly to recent calls for stronger linkage between digital measurement, training transfer, and front-line supervisory action in construction safety practice [43–51].

3. Materials and Methods

This study was designed as a single-site quasi-experimental field evaluation of a training intervention. The methodological approach was intended to reflect the actual comparison structure, define outcomes clearly, and avoid unsupported causal claims or standalone algorithm benchmarking.

3.1. Study Design and Setting

This study used a single-site, non-randomized sequential-cohort quasi-experimental design. Two consecutive groups of newly hired workers following the same onboarding pathway were compared. The first cohort completed the organization’s traditional onboarding program, while the subsequent cohort completed onboarding supported by the proposed application. Participants were assigned according to onboarding intake period rather than random allocation. Accordingly, the design should be interpreted as a non-randomized sequential-cohort comparison rather than as a pre–post study or a randomized trial. Time to qualification was operationalized as the elapsed calendar time from entry into the target onboarding pathway until qualification sign-off in the organization’s training records. This measure captures the full onboarding interval rather than classroom contact hours alone. Training cost was calculated using the organization’s internal costing basis applied consistently across both cohorts. Task accuracy was recorded as the percentage of correctly completed task elements at qualification assessment. Formal baseline covariates beyond new-hire status, shared task pathway, cohort membership, and common qualification target were not retained in the dataset, which is a limitation discussed later. Therefore, findings should be interpreted as associations observed under operational conditions rather than causal effects. The intervention incorporated markerless motion capture for joint key-point extraction, feature engineering,

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machine-learning-based ergonomic risk scoring, and a Lean/CI workflow linking real-time feedback to standard work, A3 actions, and auditable coaching logs. The app-supported onboarding intervention used a fixed tablet/camera for markerless motion capture. The application included a pose-estimation module for two-dimensional joint key-point extraction, a feature-engineering layer for posture and movement indicators, and a machine-learning-based ergonomic risk scoring module. Pose-estimation and image-processing functions were implemented using MediaPipe Pose (Google LLC, Mountain View, CA, USA; https://developers.google.com/mediapipe (accessed on 27 April 2026)) and OpenCV (OpenCV Team; https://opencv.org/). Machine-learning and data-processing routines were implemented using Python (Python Software Foundation, Wilmington, DE, USA; https://www.python.org/) and scikit-learn (https://scikit-learn.org/). Statistical analysis was performed using Microsoft Excel (Microsoft Corporation, Redmond, WA, USA) and Python. The pipeline was verified through unit and integration tests, pilot sessions for face validity and latency, and privacy controls that minimize raw-video retention and enforce role-based access. Effectiveness was then assessed with two sequential cohorts of new hires. Figure 3 summarizes the study design, cohort structure, intervention components, and analytical scope.

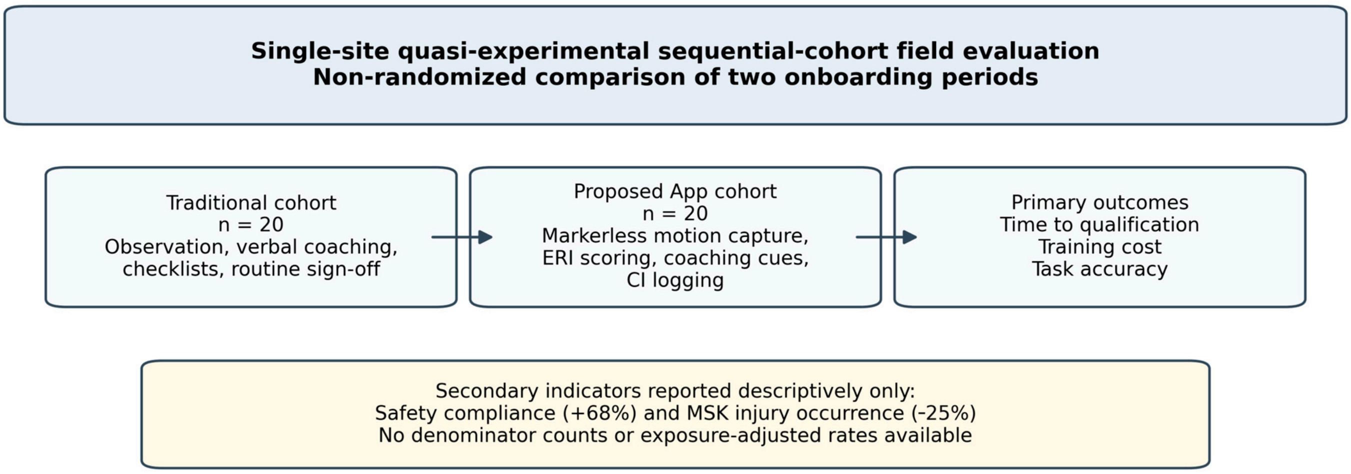

Figure 3. Study-design overview and analytical scope.

3.2. Participants and Eligibility

The study was conducted in a built-environment operational setting involving repetitive manual handling, positioning, installation, and task-sequencing activities requiring:

- Physical coordination;
- Posture control;
- Adherence to standardized procedures.

Eligible participants were newly hired workers assigned to the same role family and onboarding pathway, had not yet been certified for the target task, and were scheduled to complete the standard qualification process at the study site. The intent of this eligibility rule was to hold the qualification target constant across cohorts. Because the study relied on operational training records, no additional demographic or exposure-matched baseline dataset was available for statistical adjustment.

3.3. System Architecture

The traditional onboarding pathway relied on supervisor observation, verbal coaching, routine checklisting, and periodic competency review. The app-supported pathway retained those managerial functions but added a structured sensing-and-feedback loop.

During training sessions, a fixed camera or tablet captured worker movement, a pose estimation engine extracted two-dimensional body key points, and pose-derived features were converted into an ergonomic risk signal. When smoothed risk estimates exceeded task-specific thresholds or when risky movement patterns persisted, the system issued a brief coaching cue to the trainer and logged the event for follow-up.

The intervention closed the loop by linking each detected coaching opportunity to standardized CI actions. Session summaries were stored as auditable training records, and notable recurrent risks could be translated into standard work updates, A3 problem solving prompts, or workstation and method adjustments. In this way, the app functioned as a decision-support layer for coaching and continuous improvement rather than as an autonomous replacement for supervisors. Figure 4 illustrates the closed-loop workflow linking ergonomic sensing, coaching prompts, and continuous-improvement follow-up actions.

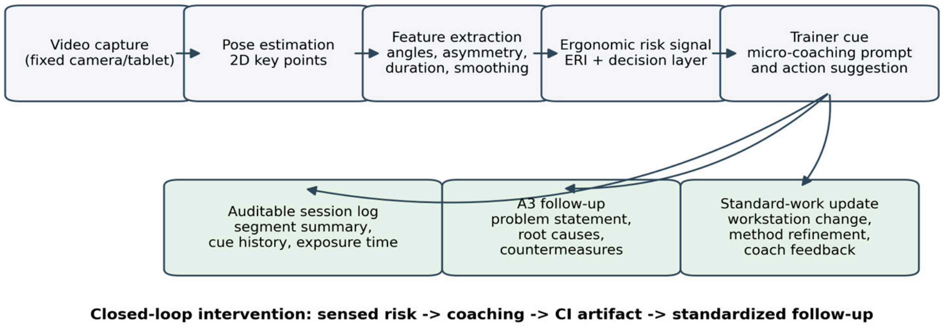

Figure 4. Closed-loop training workflow linking ergonomic sensing, coaching, and CI follow-up.

The application consists of four functional layers: (1) acquisition and pose estimation; (2) feature extraction and ergonomic risk scoring; (3) learning-based risk classification and feedback; and (4) Lean/CI integration and records.

1. Acquisition and pose estimation: markerless video capture (fixed tablet/camera) runs a pose estimation engine to obtain 2D joint key points and derived angles.
2. Feature extraction and ergonomic risk scoring: posture features (e.g., trunk/neck/upper-limb angles, asymmetry, duration) are mapped to a normalized ergonomic risk index (ERI) informed by RULA/REBA style heuristics and prior ergonomic risk-assessment methodologies [11–15].
3. Learning-based risk classification and feedback: a lightweight ML scorer converts features to risk class and personalized recommendations (micro coaching cues; suggested Lean tools).
4. Lean/CI integration and records: results are linked to standard work, A3 forms, and checklists, closing the measure $\rightarrow$ decide $\rightarrow$ act $\rightarrow$ control loop. Figures also depict the database ER diagram and the end to end flow used during training sessions.

The application used a lightweight supervised classification model trained on posture-derived features extracted from markerless motion capture. Inputs included trunk inclination, neck flexion, upper-limb elevation, asymmetry, repetition rate, and task duration indicators. The model classified movement segments into low-, moderate-, or high-risk ergonomic states. Similar ML-supported ergonomic assessment and activity-recognition approaches have been reported in prior occupational-safety and intelligent-monitoring literature [23,27,28]. To improve stability during live deployment, rolling-window smoothing and rule-based persistence thresholds were applied before prompting trainers. When elevated risk persisted beyond predefined task-specific thresholds, the system generated short coaching cues (e.g., reduce trunk flexion, reposition material, adjust reach distance).

Logged recurrent issues were later reviewed during Lean/CI meetings to support standard work refinement and A3 follow-up actions. Because the purpose of the present study was intervention evaluation rather than algorithm benchmarking, only the operational logic of the deployed model is emphasized. The primary contribution lies in how ergonomic risk classification is operationalized into real-time coaching cues, standardized work adjustments, and A3 problem solving workflows—bridging human factors assessment with actionable organizational change. Table 3 below summarizes selected ML methods chosen based on their widespread use in ergonomic classification, activity recognition, posture analysis, anomaly detection, and industrial AI applications reported in recent literature [23,27,28]. Figure 5 illustrates the overall application structure, including the user interface, data-processing components, machine-learning modules, and information data stores.

Table 3. Summary of ML methods and limitations.

Method	Strengths	Limitations
Random Forest	Robust to noise, provides feature importance	Poor temporal modeling
SVM	Effective in high-D spaces, versatile kernels	Sensitive to parameters
CNN	Automatic feature extraction, image processing	Computationally intensive
LSTM	Temporal modeling, RUL prediction	Long training times
Autoencoder	Anomaly detection, unsupervised	False positives
Transformer	Multivariate analysis, attention	High resource needs

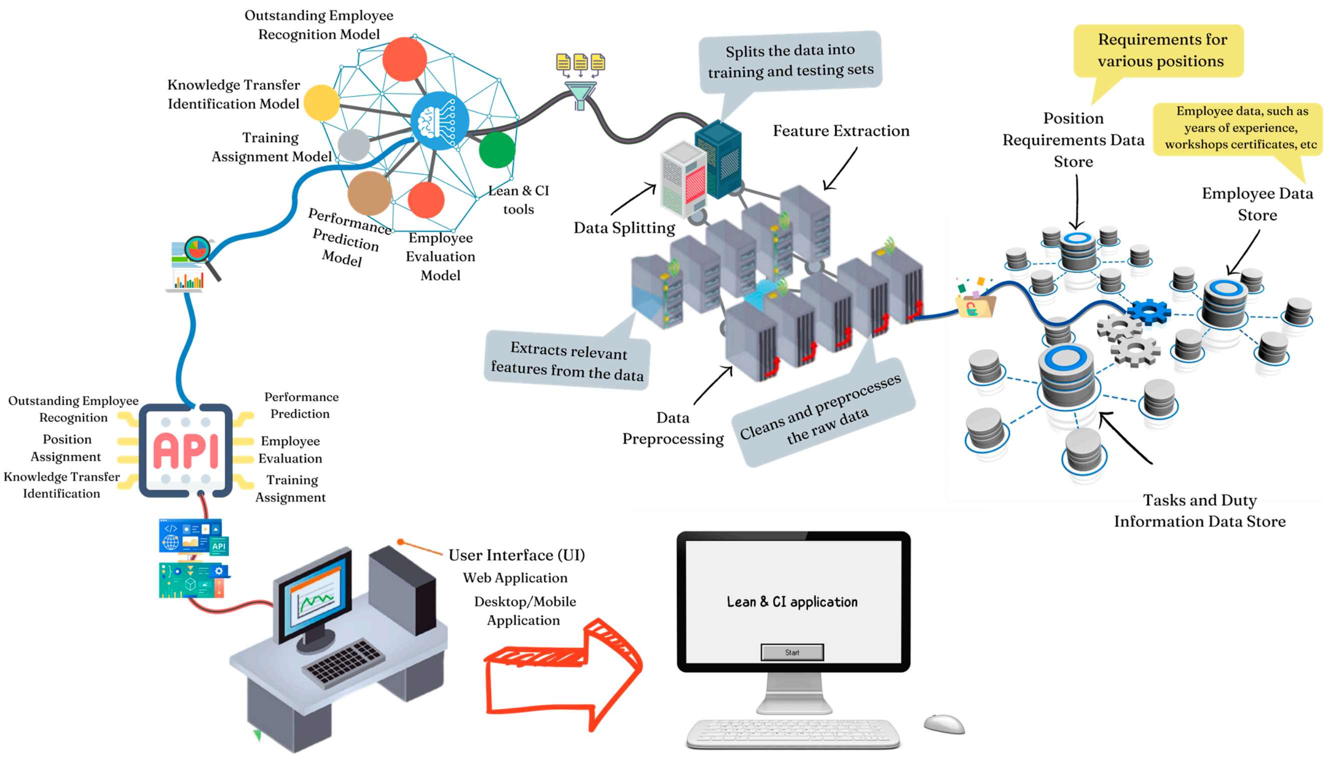

Figure 5. The application structure.

3.4. Technology Implementation

The application was implemented through a staged change management approach. Coaches first configured task templates and reviewed how to interpret the ergonomic risk index (ERI), cue prompts, and linked CI actions. An advisory-only familiarization period was then used so that trainers could observe system prompts without using them for grading decisions. After this calibration period, the app-supported workflow was used during live onboarding sessions, and weekly CI huddles reviewed recurrent risks, standard work issues, and logged countermeasures.

Each of the following phases is carefully structured to ensure the development of an effective, user-centered, and practical tool that improves workplace safety and operational efficiency.

1. Design Phase: Definition of user requirements, task analyzes, and interface layouts based on field observations and stakeholder input.
2. Development Phase: Integration of motion capture, ML scoring, and database modules within a unified Lean/CI framework.
3. Testing Phase: Validation of performance through pilot sessions, latency checks, and privacy control verification.

Deployment Phase: Implementation within live work environments, followed by evaluation of task accuracy, safety compliance, and ergonomic results. The real-time ergonomic feedback workflow is summarized in 3.5 Core Algorithm.

The application was designed to be user-friendly and does not require specialist expertise. Users of the application select their industry, and then they will be able to explore a variety of Lean and continuous-improvement tools associated with their industry, as shown in Figures 6 and 7 below.

Figure 6. Application main page.

3.5. Core Algorithms

The application used a real-time ergonomic feedback workflow to convert pose-derived movement features into coaching cues and continuous-improvement actions. During each training session, the system acquired video frames, extracted body key points, computed ergonomic features, estimated the ergonomic risk index (ERI), and generated coaching prompts when elevated risk persisted. The workflow design was informed by prior studies in ergonomic sensing, AI-assisted safety monitoring, and Lean-integrated operational feedback systems [18–20,23–28]. The real-time ergonomic feedback workflow is summarized in Algorithm 1.

Algorithm 1. Real-time ergonomic feedback loop

- Acquire frame → run pose model → key points
- Compute features (angles, symmetry, reach, repetition) and smooth over 1–3 s;
- Map features to ERI and to a risk class via ML
- If ERI $\geq$ threshold or a risky pattern persists, emit a coaching cue (e.g., "reduce trunk flexion") and suggest a Lean action (e.g., adjust standard work, 5S workstation)
- Log segment summaries (mean ERI, exposure time, cue type) to the database and update the live dashboard
- On session close, generate an A3 draft with problem statement, wastes/risks, and proposed countermeasures

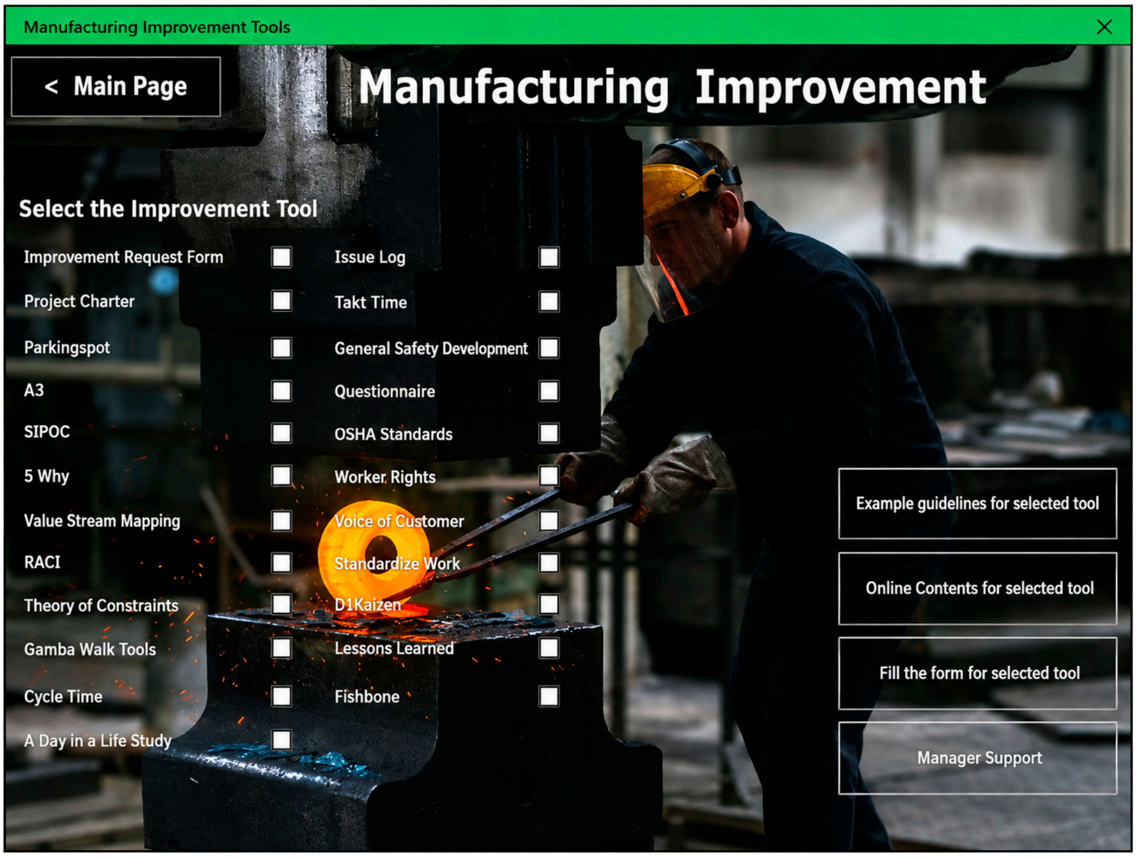

Figure 7. Manufacturing industry main page.

3.6. Data Management, Privacy, and Ethics

The study used operational onboarding data collected within normal training activities. Participants were informed that posture-derived analytics could be used for training improvement purposes. No employment decisions were based solely on automated outputs. Data were anonymized before analysis. To reduce privacy exposure, the system prioritized storage of posture-derived features and session summaries rather than routine retention of raw video. Access to any video-derived material was restricted to authorized personnel and handled according to institutional confidentiality requirements.

3.7. Testing and Validation

We combined unit/integration tests for the pipeline, face validity checks with safety managers, and pilot sessions to confirm cues were actionable and not distracting. Reliability was assessed by repeating tasks across days and verifying consistent ERI patterns on unchanged setups.

3.8. Evaluation Plan (Study Design and Statistics)

Independent-group comparisons between the traditional and proposed cohorts were conducted using two-sided Welch's t-tests due to unequal variances. For each primary outcome, we report mean differences, 95% confidence intervals, p-values, Hedges's g effect sizes, and point-biserial correlation coefficients (r). Secondary indicators (safety compliance and MSK injury changes) are reported descriptively only.

3.9. Implementation and Training (Change Management)

We developed a change management plan focused on coach empowerment and low friction adoption as follows.

- First, the site team configured industry-standard work templates and risk thresholds in the app, then held a brief orientation on reading the ergonomic risk index (ERI), interpreting on-screen cues, and opening A3/standard work links from within a session.
- Next, coaches ran shadowed practice sessions with an advisory-only week in which cues were displayed but not used for grading, to build trust and calibrate thresholds. Go-live introduced weekly CI huddles to review session logs, update standard work, and capture countermeasures.
- Adoption and training quality were monitored using built-in KPIs sessions per coach, cue-acknowledgment rate, A3s opened from cues, average ERI exposure per task, and time-to-competence with quick-reference job aids embedded in the UI.
- Access is role-based, raw video retention is minimized in favor of posture features, and all coaching actions are audit-logged to support compliance reviews.

This approach aligns the technical implementation with continuous-improvement routines and the user-centered design process described earlier.

3.10. Machine Learning Pipeline and Data Preprocessing

Prior to model training and evaluation, all captured posture data underwent a structured preprocessing pipeline to ensure robustness and consistency. Markerless motion capture was used to extract two-dimensional skeletal key points from video frames during training sessions. From these key points, ergonomic features were derived, including joint angles, trunk and neck flexion, upper-limb elevation, asymmetry, and task duration. Feature normalization and temporal smoothing (1–3 s windows) were applied to reduce noise and inter-individual variability. No raw video data were retained beyond processing, and only aggregated posture features were used for model input, supporting privacy-preserving deployment in live workplace environments. The processed features were used to classify ergonomic risk levels and to trigger real-time coaching feedback within the Lean/continuous-improvement workflow.

3.11. Ergonomic Classification Module

The machine-learning component was implemented as a practical decision-support module used to classify posture-derived ergonomic risk states and trigger coaching cues during onboarding sessions. The objective of the system was operational support rather than algorithm benchmarking. Accordingly, the present study emphasizes deployment logic and intervention outcomes rather than exhaustive standalone classifier-performance reporting.

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4. Results

Primary outcomes were defined as follows:

- Time to qualification: elapsed calendar time from onboarding entry until formal qualification sign-off.
- Training cost: total onboarding labor and supervision cost per trainee using the organization's internal costing basis.
- Task accuracy: percentage of correctly completed required task elements during qualification assessment.

All primary comparisons were statistically significant in the original analysis. The app-supported cohort outperformed the traditional cohort on all three primary outcomes. Mean time to qualification decreased from 18.60 ± 3.50 months to 5.85 ± 1.50 months, corresponding to a mean difference of −12.75 months and a relative reduction of 68.5%. Mean training costs decreased from SR 93,000 ± 17,348 to SR 29,250 ± 7602 per employee, a mean difference of -SR 63,750 and a relative reduction of 68.5%. Mean task accuracy increased from 60.65 ± 10.60% to 88.60 ± 5.70%, corresponding to a mean difference of +27.95 percentage points and a relative improvement of 46.1%.

Welch's *t*-tests indicated statistically significant cohort differences for time to qualification ($t = -14.97$, $df = 25.75$, $p < 0.001$), training cost ($t = -15.05$, $df = 26.04$, $p < 0.001$), and task accuracy ($t = 10.39$, $df = 29.14$, $p < 0.001$). Hedges's g values were very large in magnitude ($|g| = 3.22$ to 4.67). These values support substantial between-cohort separation in the observed sample, but they should be interpreted cautiously because standardized effect sizes can be inflated in modest samples and in non-randomized studies with large mean differences.

4.1. Inferential Tests (Welch's t-Test)

We used two-sided Welch *t*-tests to compare the traditional vs. proposed cohorts, as shown in Table 4 below, for each primary outcome. Table 4 shows the mean difference (proposed−traditional) with 95% CIs, t(df), *p*, Hedges g, and the point-biserial correlation r (with R^2). Figure 8 compares the primary outcomes between the traditional onboarding cohort and the proposed app-supported cohort.

Table 4. Welch *t*-tests for primary outcomes (Δ, 95% CI, t(df), *p*, Hedges g, r/R^2).

Outcome	Δ (Proposed−Traditional)	95% CI	Welch t (df)	*p*-Value	Hedges g	r/R^2
Training Time (months)	−12.75 months	[−14.50, −11.00]	−14.97 (25.75)	3.2×10^{-14}	−4.64	−0.95/0.90
Training Cost (SR)	−63,750 SR	[−72,455, −55,045]	−15.05 (26.04)	2.3×10^{-14}	−4.67	−0.95/0.90
Task Accuracy (%)	+27.95 pp	[22.45, 33.45]	10.39 (29.14)	2.6×10^{-11}	3.22	0.89/0.79

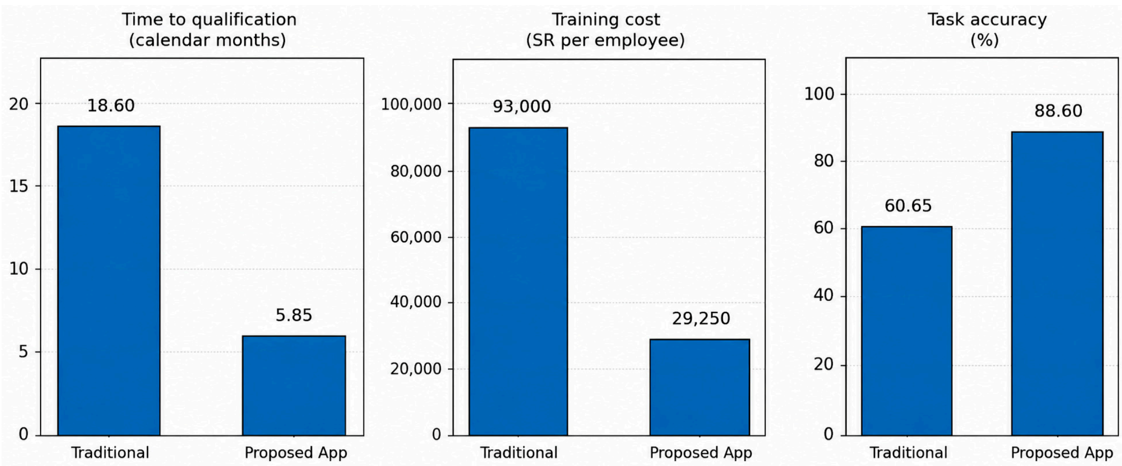

Figure 8. Cohort means for the three primary outcomes.

Figure 9 below illustrates the distribution of training time, training cost, and task accuracy across employees in the traditional and app-supported cohorts.

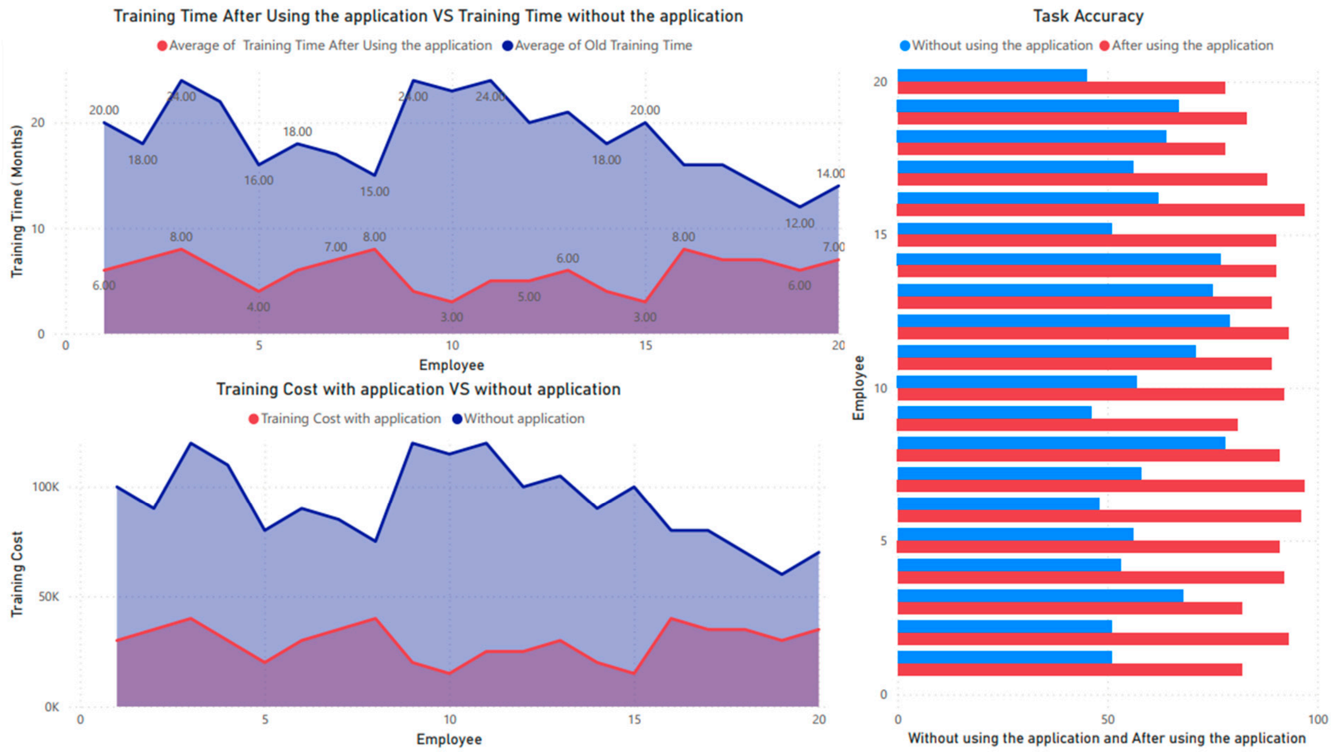

Figure 9. Traditional training approach vs. the proposed application.

4.2. Variability and Process Stability

The app-supported cohort also showed materially lower dispersion. The standard deviation for time to qualification fell from 3.50 to 1.50 months (approximately 57% lower), the standard deviation for training cost fell from SR 17,348 to SR 7602 (approximately 56% lower), and the standard deviation for task accuracy fell from 10.60 to 5.70 percentage points (approximately 46% lower). Although these reductions do not by themselves prove a causal mechanism, they are consistent with a more standardized onboarding process in which coaching cues and follow-up actions were applied more systematically.

- Time SD 3.50 $\rightarrow$ 1.50 months (-57%);
- Cost SD 17,348 $\rightarrow$ 7603 SR (-56%);
- Accuracy SD 10.60 $\rightarrow$ 5.70 pp (-46%).

4.3. Secondary Indicators: Compliance and MSK Injuries

Secondary indicators were:

- Safety compliance: site-level percentage compliance with required observed safety practices.
- MSK injury occurrence: reported musculoskeletal injury events during the observation period.

Safety compliance improvements and reduced MSK indicators were observed at the site level. During the study period, site-reported safety compliance improved by 68% and site-reported MSK injury occurrence decreased by 25%. Because denominators and exposure-adjusted data were unavailable, these findings are descriptive only and should not be interpreted inferentially.

5. Discussion

The findings suggest that integrating ergonomic sensing into structured onboarding may improve learning speed, consistency, and operational efficiency. These findings align with prior research demonstrating that immediate feedback, immersive learning support, and AI-assisted ergonomic monitoring can improve training transfer and hazard-recognition performance in construction and industrial environments [18–20,44–50]. A plausible mechanism is that real-time objective cues enable faster correction of unsafe or inefficient movement patterns, while Lean routines ensure that lessons learned are standardized and retained. Built-environment organizations typically require low-friction tools that can fit variable site conditions, short coaching windows, and accountability requirements. The intervention described here attempts to meet those constraints by converting risk signals into short coaching prompts, linking those prompts to existing Lean artifacts, and reducing privacy exposure through posture-feature retention. This interpretation is consistent with recent construction safety training studies showing that interactivity, immediate feedback, telepresence, and hazard recognition personalization can materially influence learning effectiveness and training transfer [46,48–50].

The magnitude of the raw mean differences is operationally meaningful, especially for time to qualification and direct training cost. At the same time, the very large standardized effect sizes should not be overinterpreted. In small or modest samples, standardized metrics such as Hedges's g can appear unusually large when means are far apart and within-group variability is limited. For this reason, the revised manuscript emphasizes transparent reporting of means, standard deviations, and confidence intervals rather than relying on effect-size magnitude alone.

5.1. Implementation Considerations for Built-Environment Work

The study suggests that digital ergonomics can be most useful when it is embedded in supervisory and CI routines [21–29], rather than deployed as an isolated analytics layer. Built-environment organizations typically require low-friction tools that can fit variable site conditions, short coaching windows, and accountability requirements. The intervention described here attempts to meet those constraints by converting risk signals into short coaching prompts, linking those prompts to existing Lean artifacts, and reducing privacy exposure through posture-feature retention.

The approach may be particularly relevant in environments where new workers perform repetitive or posture-sensitive manual tasks and where ramp-up time affects both safety exposure and labor cost. However, deployment outside the present site will require adaptation to lighting, occlusion, task geometry, supervision practices, worker acceptance, and local governance rules governing video-based monitoring.

5.2. Limitations

Key limitations include: First, the evaluation was conducted at a single site using sequential cohorts rather than random assignment, which limits internal validity and leaves the results vulnerable to historical confounding. Differences in supervision, staffing, workload, equipment availability, work mix, or organizational learning across time could have influenced the observed outcomes. Second, the dataset did not preserve a richer set of baseline worker covariates, which limited formal cohort comparability analysis. Third, safety compliance and MSK injury indicators were available only as aggregate site-level percentage changes without denominator counts, exposure data, or confidence intervals. These measures therefore provide descriptive context only.

6. Conclusions

This study evaluated a data-driven onboarding intervention integrating markerless motion capture, ergonomic risk scoring, machine-learning-assisted coaching prompts, and Lean/continuous-improvement routines in a built-environment setting. The app-supported cohort was associated with faster qualification, lower training cost, and higher task accuracy than the traditional cohort. These findings should be interpreted cautiously given the modest sample and non-randomized design. The proposed framework appears promising as a practical supervisory support tool, and future multi-site controlled studies with richer baseline covariates and longer follow-up are recommended.

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