# Personalized and Adaptive Virtual Reality Training for Physically Coupled Robots in Construction

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**Abstract –**

**Work-related musculoskeletal disorders (WMSDs) significantly impact worker health and productivity in construction. Physically coupled robotics, such as exoskeletons, offer a promising solution by augmenting human capabilities and reducing strain. However, their effective use requires precise human-robot synchronization, which can be challenging in dynamic construction environments. Traditional training methods often fail to address these complexities, leading to suboptimal performance, misuse, or increased injury risk. To overcome these challenges, this study develops a personalized Virtual Reality (VR) training platform incorporating an Individualized Bayesian Knowledge Tracing (iBKT) framework. The system continuously evaluates user performance in key body regions, waist, knee, and shoulder, using real-time metrics to dynamically adjust task difficulty, training frequency, and instructional feedback. This adaptive approach tailors training content to enhance motor coordination and postural control in exoskeleton-assisted tasks. Results indicate that ATG achieved greater reductions in postural errors across tasks, with total ER decreasing by 6, 3, and 5 points for walking, bending, and squatting, respectively, compared to 4, 2, and 5 points in TTG. These findings underscore the importance of adaptive, personalized training in enhancing human-robot interaction, safety, and productivity. By equipping workers with tailored skills, this study advances workforce-robot collaboration, fostering more resilient and efficient construction practices.**

**Keywords –**

**Physically coupled robots; Adaptive training; Virtual Reality**

## 1 Introduction

Work-related musculoskeletal disorders (WMSDs) represent a significant health concern in the construction industry, where physically demanding tasks are routine. Over 20% of nonfatal injuries in construction result from WMSDs, highlighting the heightened physical strain and risks associated with construction work [1]. Research shows that over 43% of construction workers report chronic musculoskeletal pain, which has been directly linked to reduced productivity, higher rates of absenteeism, and escalating healthcare costs [2]. Furthermore, the physically intensive nature of construction tasks exacerbates the risk of cumulative trauma disorders, impacting not only the physical well-being of workers but also the efficiency and cost-effectiveness of construction operations [3]. Addressing these challenges with innovative technological solutions has thus become a priority to improve both worker health and productivity in this high-risk industry.

Physically coupled robotic systems, such as exoskeletons and collaborative lifting aids, offer promising solutions to mitigate the high incidence of WMSDs within construction[4]. By directly enhancing human strength and endurance, these systems support workers in performing physically demanding tasks, such as heavy lifting, repetitive movements, and sustained awkward postures, without the same level of physical strain [5]. Unlike traditional assistive devices, physically coupled robots operate in close synchronization with human operators, offering seamless support that adapts dynamically to the user's movements. Exoskeletons, for instance, designed for leg support can reduce muscular fatigue up to 71.5% [6], a benefit that has shown potential in experimental studies to improve workers' endurance in repetitive tasks. However, fully realizing their benefits depends on highly coordinated human-robot interactions, where human movement is synchronized with robotic support to optimize safety and productivity [7].

Unlike robots in controlled industrial settings, working with physically coupled robots on construction sites requires workers to adapt control to unpredictable, site-specific conditions [8]. Successful operation of these robots relies on seamless coordination between humans and machines, where workers need the skills to adjust movement patterns, manage force distribution, and respond dynamically to real-time construction challenges. This complex, close-coupling demands specialized training to ensure workers are equipped to handle the nuanced control and adaptability needed to maximize the potential of these robots.

Traditional training programs are generally characterized by their formulaic and rigid structure, focusing on standardized methods and broad, theory-based instruction. These programs often emphasize repetition and adherence to fixed protocols, which can be effective for routine tasks but fall short in addressing the complexities of dynamic and evolving work environments. A key limitation of such approaches is their lack of flexibility and adaptability, making them ill-suited for preparing workers to navigate the nuanced demands of human-robot interaction in physically coupled systems. While theoretical robotic operations may be addressed, these programs often lack the targeted specificity and adaptability essential for real-world scenarios that demand precise, synchronized human-robot collaboration required by physically coupled robots in close-coupling applications. This gap highlights an urgent need for research-driven training solutions that go beyond traditional approaches, offering adaptable training methods tailored to worker's skills and progress.

In response, this paper presents an adaptive VR-based Human Robot Interaction (HRI) training platform specifically designed for physically coupled robots in construction. Utilizing an Individualized Bayesian Knowledge Tracing (iBKT) framework, the platform continuously evaluates each worker's performance on essential skills, dynamically adjusting the training content and pace in real-time. This adaptive approach creates a personalized learning experience that enables workers to develop a deeper understanding of the precise techniques required for effective close coupling with physically coupled robots. By simulating construction scenarios within a virtual environment, this adaptive training approach allows workers to build practical HRI skills and refine their interaction techniques with physically coupled robots, ultimately facilitating a safer and more efficient human-robot partnership on construction sites. Through this adaptive VR-based training platform, the study aims to demonstrate the effectiveness of personalized, adaptive training in reducing safety risks, and advancing the integration of physically coupled robots in construction.

## 2 The Emergence of Physically Coupled Robots in Construction: Amplifying Human Capability

Physically coupled robots are specifically engineered to operate in direct physical contact with human operators, enhancing human strength, endurance, and precision in ways that expand the range of tasks workers can perform [9]. Unlike traditional industrial robots, which function autonomously or semi-autonomously, physically coupled robots are deeply integrated with the user, forming a symbiotic relationship that merges human intuition with robotic power to increase productivity and efficiency [10]. Exoskeletons are a prominent and widely adopted example of physically coupled robots. These wearable devices are designed to augment human physical abilities by providing mechanical support during strenuous tasks [11]. Working in close coordination with the human body, exoskeletons function as an extension of the user's own movements, enhancing strength, endurance, and precision. This makes them particularly valuable in environments involving repetitive, heavy, or physically demanding tasks.

The construction industry is especially positioned to benefit from this form of human-robot collaboration. Given the labor-intensive and physically demanding nature of many construction tasks, physically coupled robots can significantly reduce physical strain, minimize injury risk, and improve operational efficiency. Tasks that require heavy lifting, repetitive actions, or prolonged exertion can be performed more safely and effectively with exoskeleton assistance [12]. These devices amplify the user's strength, stabilize posture, and reduce fatigue, ultimately enhancing task performance and reducing physical stress on workers.

However, the integration of physically coupled robotics, such as exoskeletons, into construction introduces challenges [13]. Unlike conventional assistive tools, these systems require active human engagement, demanding continuous adjustment and synchronization of worker movements with robotic assistance. Improper usage, such as misaligned movement patterns or incorrect force distribution, can result in inefficient task execution, discomfort, or heightened physical strain, ultimately diminishing the intended benefits of these technologies. Consequently, equipping workers with the requisite motor coordination, adaptive control strategies, and cognitive decision-making skills is crucial for the safe and effective deployment of these systems. To achieve this, structured training programs are indispensable, ensuring that workers receive personalized, responsive instruction that enhances their ability to integrate these robotic systems seamlessly into dynamic construction workflows. Traditional training programs, typically formulaic and rigid, lack the specificity needed for these dynamic environments [14]. This limitation highlights the need for adaptive training solutions that personalize the learning experience, equipping workers with the skills necessary for effective interaction with wearable robotic systems in real-world construction scenarios.

# 3 The Need for Adaptive Training in Physically Coupled Robotics

Adaptive training is defined as a method in which the problem, stimulus, or task adjusts dynamically based on the trainee's performance [15]. Unlike conventional, static approaches, adaptive training dynamically customizes adaptive variables through a defined adaptive logic that continuously monitors performance metrics. This real-time adjustment creates a highly personalized learning experience, enhancing both efficiency and effectiveness. Performance metrics are indicators of a trainee's current skill level and progress, such as movement accuracy, reaction times, task completion rates, and overall accuracy. These metrics are gathered either through ongoing assessments that provide immediate feedback or post-session evaluations to measure overall progress. These metrics feed into the adaptive logic, which determines how and when to adjust adaptive variables, such as simulation difficulty or feedback type, to keep training optimally aligned with the trainee's evolving needs [16].

Adaptive training methodologies have found widespread application in industries including construction, adaptive training has been employed to improve worker safety, skill development, and operational efficiency. Studies have developed personalized safety training programs that dynamically adjust hazard recognition tasks based on workers' prior performance and learning progress, leading to enhanced hazard identification and risk mitigation capabilities [17]. In labor-intensive construction tasks, adaptive methods have been utilized to modify task difficulty in real time based on ergonomic assessments, resulting in improved lifting techniques and a reduction in musculoskeletal strain [18]. Additionally, cognitive training frameworks in construction have employed adaptive approaches to tailor problem-solving complexity to individual proficiency levels, thereby enhancing situational awareness and decision-making in dynamic work environments.

Previous research has demonstrated that adaptive training enhances learning efficiency and y, knowledge retention, and task-specific skill acquisition by dynamically adjusting instruction based on user performance metrics. Given the specific demands of exoskeleton training, such as the need for precise movement synchronization, optimized force distribution, and adaptive cognitive control, workers could greatly benefit from adaptive training approaches that tailor instruction to their biomechanics and real-time interaction with robotic assistance. However, research specifically focusing on adaptive training for physically coupled exoskeleton systems remains limited.

This study aims to develop an adaptive training solution to enhance human-robot collaboration in physically coupled robotics for construction. Given the need for training that adapts to individual learning progress, dynamically modifies task complexity, and provides real-time feedback on movement synchronization and force distribution, Virtual Reality (VR) serves as an effective platform [19]. Its immersive and interactive environment enables controlled, data-driven adjustments to training parameters within diverse construction scenarios that enhance adaptability.

To achieve this, the research focuses on developing a framework that continuously monitors, evaluates, and adjusts training variables based on real-time performance metrics, including movement synchronization, force distribution, and task-specific coordination. By integrating adaptive logic with VR, this study seeks to replicate the dynamic conditions of construction sites, addressing a critical gap in training methodologies and facilitating the broader adoption of wearable robotics in the industry.

# 4 Method: Development of Adaptive Training Platform for Enhancing Human Physically Coupled Robot Interaction in Construction

The VR-based adaptive training system for worker-physically coupled robot interaction is a data-driven approach to improve learning efficiency and optimize task mastery. The system relies on performance metrics to capture real-time motion data from user movements, which are processed by the iBKT-based adaptive logic to analyze the user's task mastery probabilities (Figure 1). When these probabilities exceed a predefined threshold, the system dynamically adjusts adaptive variables, such as task difficulty and task frequency, within the VR training environment. These adjustments are tailored to challenge the user appropriately while preventing skill stagnation, ensuring that users can master the required skills effectively and efficiently.

## 4.1 Performance Metrics

Key performance metrics were established to evaluate workers' capabilities in worker-physically coupled robot interaction, with a focus on movement accuracy as indicators of effective collaboration. Body angles were selected as the primary indicator of movement accuracy, measured through motion tracking sensors from Inertial Measurement Units (IMUs) and Lighthouse Tracking system (LTS) placed on key body segments, including the waist, knee and shoulder. These IMU sensors continuously monitor, enabling real-time analysis of worker posture and alignment within the robotic system. To mitigate drift errors commonly associated with IMUs, a sensor fusion approach integrating LTS data was employed to provide periodic corrections, ensuring long-term accuracy. Additionally, drift compensation algorithms, including zero-velocity updates and complementary filtering, were applied to correct accumulated errors over time. To accurately assess movement accuracy, joint angles at critical body points are calculated using vector-based computations derived from IMU data. For each body segment $\vec{u}$, it's calculated by determining the difference between the three-dimensional coordinates of the segment's endpoints $\vec{P_1}$ and $\vec{P_2}$ as $\vec{u} = \vec{P_1} - \vec{P_2}$. With segment vectors established for adjacent body parts, the joint angle $\theta$ between two connected segments $\vec{u}$ and $\vec{v}$ is then computed using the cosine rule $\theta = arccos(\frac{\vec{u}\cdot\vec{v}}{|\vec{u}||\vec{v}|})$.

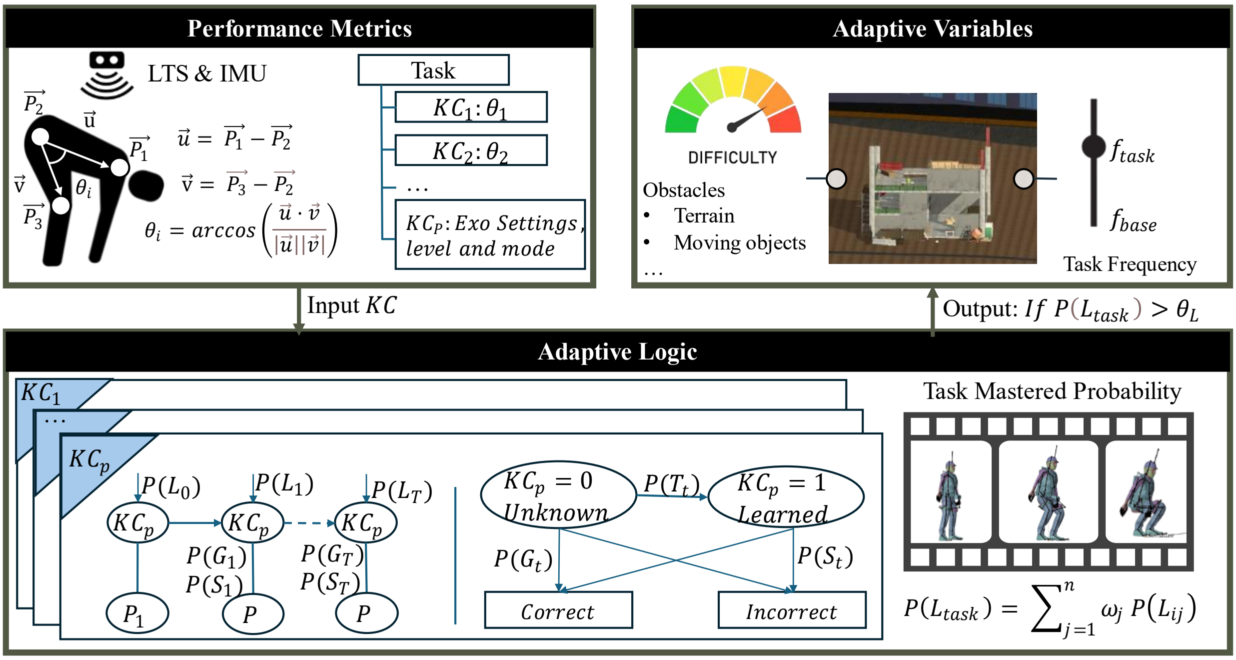


Figure 1. Overview of the developed VR-based adaptive training syste

## 4.2 Adaptive Logic

Effective adaptive training for physically coupled robotics requires a framework that continuously monitors user performance, dynamically adjusts training parameters, and personalizes learning trajectories. Bayesian Knowledge Tracing (BKT) is well-suited for this application as it models skill acquisition by estimating a learner's mastery probability and updating it based on observed performance. However, standard BKT assumes fixed learning and error probabilities, limiting its responsiveness to real-time changes in human-robot interaction. To address this, we propose an individualized BKT (iBKT) model, which dynamically updates learning probabilities based on real-time performance metrics, refining adaptation to individual learning curves and optimizing skill acquisition in exoskeleton training

The proposed iBKT model extends the traditional BKT framework by enabling real-time adaptation of key parameters based on observed learner performance, thus catering to individual characteristics. The training content is divided into knowledge components (KCs), where each KC represents key body angles extracted from the performance matrix, with a value of KC=1 indicating mastery and KC=0 indicating non-mastery. These components are selected according to ergonomic and task-specific requirements.

A preliminary test is administered in which participants complete a set of baseline tasks designed to evaluate their prior knowledge and motor coordination relevant to exoskeleton operation. This test is used to initialize four critical parameters within the iBKT model for each KC, including the initial probability that user $i$ knows KC $j$ $P(L_{0_{ij}})$; the likelihood of transitioning from a state of non-mastery to mastery of learning KC $j$ after an interaction $P(T_{ij})$; the guess probability $P(G_{ij})$, which is the probability of a correct response to a KC $j$-related question despite lack of mastery; and slip probability, $P(S_{\mathrm{ij}})$, which is the probability of an incorrect response despite mastery of the KC $j$. Due to the inherent uncertainty in the guessing and slipping behaviors, $P(G_{ij})$ and $P(S_{\mathrm{ij}})$ are assumed to follow Beta distributions, allowing for flexible and continuous adjustment based on learner performance.

After initialization, these parameters are continually updated based on the learner's real-time performance to individualize the training process. The guess and slip probabilities, $P(G_{ij})$ and $P(S_{\mathrm{ij}})$ , are updated via Bayesian inference, refining these parameters based on learner performance over time. For $P(S_{\mathrm{ij}})$, if the learner has mastered the knowledge but makes an incorrect response (indicating a slip), the posterior distribution is updated as

$$S|data \sim Beta(\alpha_S + f, \beta_S + m - f) \quad (1)$$

where $m$ represents the total number of responses in the mastered state, and $f$ is the number of incorrect responses. Similarly, $P(G_{\mathrm{ij}})$ is updated when the learner is in an unmastered state and correctly guesses the answer, with the posterior distribution.

$$G|data \sim Beta(\alpha_G + g, \beta_s + n - g) \quad (2)$$

where $n$ is the total number of responses in the unmastered state, and $g$ represents correct responses within that state.

The learning probability is $P(T_{ij})$ dynamically adjusted based on recent task performance. If the learner's recent accuracy $R$ meets or exceeds a predefined target accuracy $R_{target}$, $P(T_{ij})$ is incremented by a set step size $\Delta T$. Conversely, if $R$ falls below $R_{target}$, $P(T_{ij})$ is reduced by $\Delta T$ . $P(T_{ij})$ is updated as

$$P(T_{ij}) = \min\left(0, \max\left(1, P(T_{ij}) + \Delta T \cdot sign(R - R_{target})\right)\right) \quad (3)$$

Finally, the mastery probability $P(L_{0_{ij}})$ is updated at each time step $t$ through the forward algorithm. Given a learner's response at time $t$, the probability of correctly answering a question related to KC $j$, denoted as $P\left(C_{t_{ij}}\right)$, is calculated by

$$P\left(C_{t_{ij}}\right) = P\left(L_{t_{ij}}\right) \times \left(1 - P(S_{ij})\right) + \left(1 - P\left(L_{t_{ij}}\right)\right) \times P(G_{ij}). \quad (4)$$

Following each response, $P\left(L_{t+1_{ij}}\right)$ is updated based on whether the answer was correct or incorrect. For a correct response, the updated mastery probability is $P\left(L_{t+1_{ij}}\middle|observation = C_{t_{ij}}\right) = \frac{P\left(L_{t_{ij}}\right) \times \left(1 - P(S_{ij})\right)}{P\left(C_{t_{ij}}\right)}$ . Conversely, if the response is incorrect, the update is given by $P\left(L_{t+1_{ij}}\middle|obs = \neg C_{t_{ij}}\right) = \frac{P\left(L_{t_{ij}}\right) \times P(S_{ij})}{P\left(\neg C_{t_{ij}}\right)}$. The final mastery probability $P\left(L_{t+1_{ij}}\right)$ after time $t$ is calculated as

$$P\left(L_{t+1_{ij}}\right) = P\left(L_{t+1_{ij}}\middle|obs\right) + P(T_{ij}) \times \left(1 - P\left(L_{t+1_{ij}}\middle|obs\right)\right) \quad (5)$$

For a specific human-robot interaction task, the overall task mastery probability$P(L_{task})$ is computed by aggregating the mastery probabilities across all relevant KCs required for the task as $P(L_{task}) = \sum_{j=1}^{n} \omega_j \, P\left(L_{ij}\right)$, where $\omega_j$ is the weight of KC $j$, satisfying the condition $\sum_{j=1}^{n} \omega_j = 1$.

### 4.3 Adaptive Variables

The training platform dynamically adjusts certain human-physically coupled robot interaction task difficulty and frequency based on the user's performance on certain task, optimizing the training experience to support mastery in human-robot interaction under realistic conditions. When the learner's mastery probability $P(L_{task})$ for a specific task reaches or exceeds a predefined threshold $\theta_T$, indicating sufficient proficiency, the model increases task difficulty by introducing additional construction-related obstacles, such as uneven terrain or moving objects, to simulate the dynamic and unpredictable nature of a real-world construction environment. This adjustment helps further challenge the learner and prevent skill stagnation. To ensure task diversity and avoid overexposure to a single task, the model employs a rotation mechanism that varies task frequency $f_{task}$ based on mastery levels. Task frequency $f_{task}$ is adjusted according to the function.

$$f_{task} = f_{base} \cdot \left(1 - \alpha \cdot \frac{P(L_{task}) - \theta}{1 - \theta}\right) \quad (6)$$

where $f_{base}$ is the base frequency of task rotation, and $\alpha$ is a scaling factor that controls how rapidly the task frequency decreases as $P(L_{task})$ approaches 1. This rotation mechanism ensures a balanced distribution of tasks across all relevant KCs, while placing greater emphasis on those areas that require further development, thus promoting well-rounded proficiency.

## 5 Case Study: Evaluating the Effectiveness of Adaptive HRI Training Platform

The adaptive training platform was developed in a virtual reality (VR) environment using Unity [20] and deployed on the VIVE PRO 2 [21] system. To enable real-time tracking of body movements, SteamVR motion trackers were attached to each participant, allowing the platform to dynamically adjust training variables based on real-time body position data.

To evaluate the effectiveness of the adaptive training platform for exoskeleton operation, a case study was conducted with a diverse group of 30 participants with varying backgrounds and skill levels. Participants ranged from novice users with no prior exoskeleton experience to experienced operators. To control prior knowledge, participants were evenly divided into two groups based on their experience: the Adaptive Training Group (ATG), which received training through the iBKT-based adaptive platform, and the Traditional Training Group (TTG), which underwent standard, non-adaptive training. To ensure an accurate assessment of each participant's skill improvement, all participants first completed a pre-assessment to establish baseline task score in exoskeleton operation. The tasks include walking, bending, and squatting. During the process, each participant was instructed to perform the designated tasks while motion tracking sensors recorded joint angles and movement trajectories. The collected data was processed to calculate error rate (ER) metrics, which quantified deviations in posture and movement accuracy based on REBA scoring criteria [22], which assesses postural risks by assigning scores to different body regions. ER is calculated by quantifying deviations in key body joints, including shoulders, waist, and knees, and mapping these deviations to corresponding REBA risk levels. Following the pre-assessment, participants engaged in training according to their group assignment. Upon completing the training, participants were evaluated using the same ER metrics as in the pre-assessment.

# 6 Results

The effectiveness of the adaptive VR training platform was evaluated by comparing the mastery probability $P(L_{task})$ progression and error rates (ER) between the ATG and TTG across the training period.

## 6.1 Task Mastery Probability Progression

Figure 2 illustrates the progression of mastery probabilities over the training sessions for a randomly selected participant from the ATG. Three commonly encountered tasks in construction and main body joint mastery probabilities in each task are recorded. The upper panel of the figure (3 × 13 grid) depicts the evolution of the proficiencies of three KCs, $P(L_j)$, and the lower panel (3 × 13 grid) illustrates the progression of trained task proficiencies, $P(L_{Task\_i})$, across 13 training sessions. From the figure, tasks with fewer correct attempts appear more frequently in the training sequence, ensuring the participant receives sufficient practice opportunities to reinforce weaker areas. The proficiencies in both panels reveal a clear upward trend, reflecting the gradual improvement in mastery levels for both knowledge components and tasks, driven by the adaptive nature of the training system.

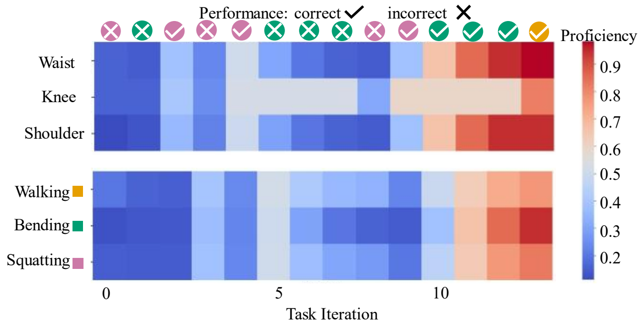


Figure 2. An example of the iBKT-based adaptive training process

## 6.2 Task Score Comparison

Figure 3 illustrates the pre- and post-training error rates (ER) for the targeted tasks—walking, bending, and squatting, broken down by body parts for the Adaptive Training Group (ATG) and the Traditional Training Group (TTG). For walking, the total ER for ATG decreased from 9 (waist: 7, knee: 2) to 3 (waist: 1, knee: 2), showing a reduction of 6 points. TTG also improved, with total ER decreasing from 8 (waist: 7, knee: 1) to 4 (waist: 3, knee: 1), a reduction of 4 points.
For bending, ATG's total ER decreased from 7 (waist: 2, shoulder: 5) to 4 (waist: 2, shoulder: 2), reflecting a 3-point improvement. TTG also showed a 2-point reduction, with total ER decreasing from 7 (waist: 3, shoulder: 4) to 5 (waist: 3, shoulder: 2). For squatting, ATG's total ER improved significantly, decreasing from 8 (waist: 4, knee: 3, shoulder: 1) to 3 (waist: 1, knee: 1, shoulder: 1), a reduction of 5 points. TTG's total ER decreased from 10 (waist: 4, knee: 4, shoulder: 2) to 5 (waist: 2, knee: 2, shoulder: 1), showing a reduction of 5 points. These results indicate that ATG exhibited greater reductions in postural errors across tasks, particularly in waist and shoulder alignment, with higher total score reductions compared to TTG. This suggests that the adaptive nature of the training platform contributed to more substantial improvements in movement accuracy and postural control. The observed enhancements in waist and shoulder positioning are particularly relevant, as these areas are critical for exoskeleton operation, influencing overall balance and load distribution. The ability of the system to dynamically modify task difficulty and provide real-time feedback likely played a key role in refining postural strategies and improving motor coordination.

Furthermore, paired t-tests indicate that ATG participants exhibited significantly greater improvements in knee ($p=0.0004$), shoulder ($p<0.0001$), and waist ($p=0.0001$) error rates across walking, bending, and squatting tasks, respectively. Independent t-tests further confirm that post-training ER values were significantly lower in ATG than TTG ($p<0.05$), demonstrating the superior effectiveness of adaptive training in refining movement accuracy and postural stability in exoskeleton operation.

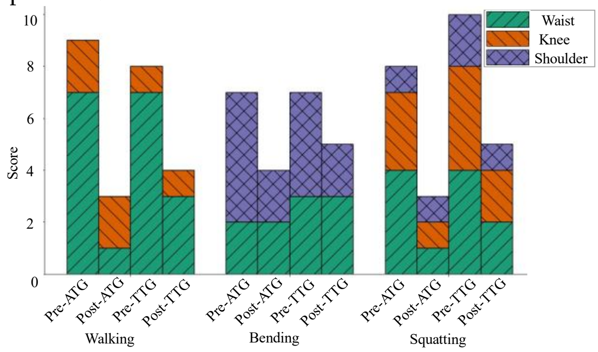


Figure 3. Pre- and Post-Training Task Scores for ATG and TTG

# 7 Conclusion

This research developed an adaptive training platform using the Individualized Bayesian Knowledge Tracing (iBKT) framework to enhance HRI skills for construction workers operating physically coupled robots, such as exoskeletons. The platform provided personalized, real-time adjustments to training content, effectively addressing individual performance gaps and ensuring efficient skill acquisition. Results demonstrated that the adaptive training led to steady improvement in task mastery and showed significant advantages compared to traditional training. This study underscores the importance of adaptive training in optimizing human-robot collaboration, particularly in dynamic and demanding construction environments.

However, several limitations remain. The current study was conducted in a simulated VR environment without real-world validation using physical exoskeletons, necessitating future studies to assess its practical applicability. Additionally, the system was designed for individual training, and its effectiveness in multi-user collaborative settings has yet to be explored. Long-term retention studies are also required to evaluate whether skills acquired through adaptive VR training persist over time or require.

By integrating real-time feedback and immersive VR simulations, the platform allowed workers to build essential skills safely and effectively. Future research could expand on this approach by exploring other adaptive algorithms and broader applications across different types of physically coupled robots. Ultimately, this adaptive training model represents a promising direction for facilitating the integration of advanced robotics in construction.

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# References

[1] "CPWR Musculoskeletal Disorders (MSDs) in Construction." Accessed: Dec. 01, 2024. [Online]. Available: https://www.cpwr.com/research/data-center/data-dashboards/musculoskeletal-disorders-in-construction/

[2] H. Zong, W. Yi, M. F. Antwi-Afari, and Y. Yu, "Fatigue in construction workers: A systematic review of causes, evaluation methods, and interventions," *Saf Sci*, vol. 176, p. 106529, Aug. 2024, doi: 10.1016/J.SSCI.2024.106529.

[3] M. F. Antwi-Afari *et al.*, "A science mapping-based review of work-related musculoskeletal disorders among construction workers," *J Safety Res*, vol. 85, pp. 114–128, Jun. 2023, doi: 10.1016/J.JSR.2023.01.011.

[4] "Automation and Robotics in the Architecture, Engineering, and Construction Industry," *Automation and Robotics in the Architecture, Engineering, and Construction Industry*, 2022, doi: 10.1007/978-3-030-77163-8.

[5] C. Andrade and D. Nathan-Roberts, "Occupational Exoskeleton Adoption and Acceptance in Construction and Industrial Work: A Scoping Review," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 66, no. 1, pp. 1325–1329, Sep. 2022, doi: 10.1177/1071181322661415.

[6] Z. Yan, B. Han, Z. Du, T. Huang, O. Bai, and A. Peng, "Development and testing of a wearable passive lower-limb support exoskeleton to support industrial workers," *Biocybern Biomed*

*Eng*, vol. 41, no. 1, pp. 221–238, Jan. 2021, doi: 10.1016/J.BBE.2020.12.010.

[7] Y. Liu *et al.*, "Studying the Effects of Back-Support Exoskeletons on Workers' Cognitive Load during Material Handling Tasks," *Construction Research Congress 2024, CRC 2024*, vol. 1, pp. 659–669, 2024, doi: 10.1061/9780784485262.067.

[8] S. Crea *et al.*, "Occupational exoskeletons: A roadmap toward large-scale adoption. Methodology and challenges of bringing exoskeletons to workplaces," *Wearable Technologies*, vol. 2, p. e11, 2021, doi: 10.1017/WTC.2021.11.

[9] A. Ojha, Y. Gautam, H. Jebelli, and A. Akanmu, "Physiological impact of powered back-support exoskeletons in construction: Analyzing muscle fatigue, metabolic cost, ergonomic risks, and stability," *Autom Constr*, vol. 168, p. 105742, Dec. 2024, doi: 10.1016/J.AUTCON.2024.105742.

[10] S. Shayesteh *et al.*, "Evaluating the Impact of Powered Back-Support Exoskeletons and Virtual Reality Interventions on Gait Stability of Construction Workers at Heights," *Computing in Civil Engineering 2023: Resilience, Safety, and Sustainability - Selected Papers from the ASCE International Conference on Computing in Civil Engineering 2023*, pp. 392–399, 2024, doi: 10.1061/9780784485248.047.

[11] A. Ojha, H. Guo, H. Jebelli, A. Martin, and A. Akanmu, "Assessing the Impact of Active Back Support Exoskeletons on Muscular Activity during Construction Tasks: Insights from Physiological Sensing," *Computing in Civil Engineering 2023: Resilience, Safety, and Sustainability - Selected Papers from the ASCE International Conference on Computing in Civil Engineering 2023*, pp. 340–347, 2024, doi: 10.1061/9780784485248.041.

[12] S. J. Baltrusch, F. Krause, A. W. de Vries, and M. P. de Looze, "Arm-support exoskeleton reduces shoulder muscle activity in ceiling construction," *Ergonomics*, Nov. 2023, doi: 10.1080/00140139.2023.2280443.

[13] S. Shayesteh, A. Ojha, Y. Liu, and H. Jebelli, "Human-robot teaming in construction: Evaluative safety training through the integration of immersive technologies and wearable physiological sensing," *Saf Sci*, vol. 159, p. 106019, Mar. 2023, doi: 10.1016/J.SSCI.2022.106019.

[14] M. J. Burke, S. A. Sarpy, K. Smith-Crowe, S. Chan-Serafin, R. O. Salvador, and G. Islam, "Relative effectiveness of worker safety and health training methods," *Am J Public Health*, vol. 96, no. 2, pp. 315–324, Feb. 2006, doi: 10.2105/AJPH.2004.059840.

[15] C. R. Kelley, "What is Adaptive Training?1," *https://doi.org/10.1177/001872086901100602*, vol. 11, no. 6, pp. 547–556, Dec. 1969, doi: 10.1177/001872086901100602.

[16] M. Zahabi and A. M. Abdul Razak, "Adaptive virtual reality-based training: a systematic literature review and framework," *Virtual Real*, vol. 24, no. 4, pp. 725–752, Dec. 2020, doi: 10.1007/S10055-020-00434-W/FIGURES/5.

[17] W. Li, H. Huang, T. Solomon, B. Esmaeili, and L. F. Yu, "Synthesizing Personalized Construction Safety Training Scenarios for VR Training," *IEEE Trans Vis Comput Graph*, vol. 28, no. 5, pp. 1993–2002, May 2022, doi: 10.1109/TVCG.2022.3150510.

[18] Sudip Subedi, Nipesh Pradhananga, Armando Carrasquillo, and Francisco Lopez, "Virtual Reality-based Personalized Learning Environment for Repetitive Labor-intensive Construction Tasks." Accessed: Mar. 13, 2025. [Online]. Available: https://www.researchgate.net/

[19] S. Shayesteh, A. Ojha, and H. Jebelli, "Workers' Trust in Collaborative Construction Robots: EEG-Based Trust Recognition in an Immersive Environment," in *Automation and Robotics in the Architecture, Engineering, and Construction Industry*, Cham: Springer International Publishing, 2022, pp. 201–215. doi: 10.1007/978-3-030-77163-8_10.

[20] "Unity Real-Time Development Platform | 3D, 2D, VR & AR Engine." Accessed: Jan. 22, 2024. [Online]. Available: https://unity.com/

[21] "VIVE Pro 2 Full Kit - High-Resolution PC VR Gaming System." Accessed: Nov. 02, 2024. [Online]. Available: https://www.vive.com/us/

[22] S. Hignett and L. McAtamney, "Rapid Entire Body Assessment (REBA)," *Appl Ergon*, vol. 31, no. 2, pp. 201–205, Apr. 2000, doi: 10.1016/S0003-6870(99)00039-3.