Cognitive Load-Aware Virtual Reality Training Platform for Safe Drone Operations in Construction

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Abstract –

Drones have become indispensable in construction projects, performing tasks such as site surveying, 3D mapping, progress monitoring, and inspecting hazardous or hard-to-reach areas. Their integration has significantly enhanced efficiency, precision, and safety. However, effective human-drone interaction remains challenging due to the complexity of construction environments and the necessity for precise drone control, which requires workers to undergo extensive training. Traditional training programs primarily focus on task-specific skills, often neglecting the influence of workers' cognitive and physiological states on learning effectiveness and performance. This oversight can lead to increased cognitive fatigue, reduced learning outcomes, and heightened safety risks. To address these limitations, this study introduces a Virtual Reality (VR)-based adaptive training platform designed to optimize worker-drone interactions by monitoring cognitive load through physiological indicators such as heart rate and skin conductance. Utilizing a Long Short-Term Memory (LSTM) model, the platform accurately predicts cognitive load in real time and dynamically adjusts the training pace to align with individual cognitive states. In experimental evaluations, the adaptive training platform achieved a cognitive load prediction accuracy of 92% and reduced task completion time by 69.9%, outperforming non-adaptive training methods by 27.6% in worker-drone interaction scenarios. By personalizing the training experience based on real-time cognitive assessments, the platform enhances worker preparedness, promoting safer and more efficient drone operations on construction sites. This research underscores the critical role of integrating physiological data into adaptive training systems to meet the multifaceted demands of modern construction environments.

Keywords –

Virtual Reality; Human-Drone Interaction; Physiological signals; Adaptive training

1 Introduction

Drones, or unmanned aerial vehicles (UAVs), have revolutionized the construction industry by performing a wide array of tasks such as site surveying, 3D mapping, progress monitoring, and inspecting hazardous or hard-to-reach areas. Equipped with advanced sensors and high-resolution cameras, drones provide precise data collection from multiple angles, offering invaluable insights into onsite conditions [1]. Their versatility and adaptability to diverse environments have led to widespread adoption, transforming project management and execution into more efficient and innovative processes [2]. Studies indicate that incorporating drones into construction workflows can boost productivity by up to 94.48%, accelerate operations by 35.41%, and reduce costs by as much as 78% compared to traditional methods [3]. These improvements underscore the significant role drones play in enhancing efficiency, precision, and safety on construction sites [4].

Despite advancements in drone automation, effective deployment in construction settings still necessitates substantial human oversight. Construction sites are inherently dynamic and unpredictable, with constantly changing conditions such as weather variations, movement of workers and equipment, and shifting project requirements. While drones can autonomously execute predefined tasks, they often lack the flexibility to adapt to real-time, unforeseen changes. Complex operations like navigating confined spaces or conducting detailed inspections demand precise, context-specific control that only skilled human operators can provide [5]. This active human-drone interaction ensures that drone operations align with project objectives and adapt to the specific needs of the construction site.

The complexity of drone operation, encompassing both hardware and software components, requires operators to possess a robust foundation of theoretical knowledge and practical skills [6]. Moreover, the unpredictable nature of construction environments necessitates that drone operators are highly adaptable and capable of making swift, informed decisions to effectively address real-time challenges [7]. Consequently, comprehensive training programs are essential to prepare workers for the multifaceted demands of drone operation in construction settings. These programs aim to equip workers with the ability to operate drones safely and effectively under a variety of real-world conditions by training them to process large volumes of situational and operational information, make complex decisions, and maintain sustained concentration.

However, such intensive training requirements can significantly increase the cognitive demands on workers [8]. Cognitive load, defined as the mental effort required to process information and perform tasks, is influenced by both task complexity and individual capacity. Excessive cognitive load can impair workers' ability to process information efficiently, perform tasks accurately, and ultimately diminish the overall effectiveness of the learning process [9]. Current training systems for construction workers typically emphasize the development of task-specific skills, such as maneuvering drones or performing specialized construction-related operations [5]. While these systems have proven effective in skill acquisition for specific tasks, they often inadequately address fluctuations in cognitive load, which can significantly impact learning efficiency and task performance.

To address these limitations, this study develops and evaluates a Virtual Reality (VR)-based adaptive training platform designed to enhance worker-drone collaboration in construction environments. The system utilizes real-time physiological data, including heart rate and skin conductance, to predict users' cognitive load and dynamically adjust the complexity and frequency of training tasks accordingly. By monitoring cognitive load through physiological inputs, the platform can tailor the training experience to individual cognitive states, ensuring that workers are neither overwhelmed nor under-challenged during training. The ultimate goal of this research is to enhance worker performance and ensure safer, more efficient human-drone collaboration on construction sites. By leveraging adaptive immersive technologies, the proposed system addresses the challenges posed by dynamic construction environments, equipping workers with the necessary skills and adaptability to effectively integrate drones into modern workflows and meet the demands of increasingly complex construction projects.

2 The Multifunctional Role of Drones in Transforming the Construction Landscape

Drones, or Unmanned Aerial Vehicles (UAVs), are advanced aircraft systems designed to operate without an onboard human pilot. Equipped with advanced sensors, high-definition cameras, and GPS systems, drones can perform a variety of tasks with remarkable precision, such as capturing real-time data, generating accurate 3D models, and conducting remote inspections [10]. These features have established drones as versatile tools across multiple industries. In construction, preliminary studies and practical applications have demonstrated their potential to offer significant improvements in efficiency, precision, and safety compared to traditional methods [11]. For instance, drones are increasingly utilized in site surveys, mapping, progress monitoring, and safety inspections, indicating their growing relevance in addressing the complex demands of modern construction projects [12].

However, the integration of drones into construction workflows presents significant challenges While drones possess autonomous capabilities for executing predefined tasks, the dynamic and unpredictable nature of construction environments poses substantial safety risks. For instance, simulations recorded 773 collisions over 230 runs under autonomous control [13], underscoring the critical need for skilled operators to provide remote supervision and control. Studies have shown that worker operators trained in navigating complex terrain, managing sophisticated drone functionalities, and adapting to evolving site conditions reduce operational errors, significantly improving safety and effectiveness in drone operations [5]. This underscores the critical importance of comprehensive training programs aimed at enhancing worker-drone cooperation. Such training must encompass both theoretical understanding and practical application, emphasizing drone operation in complex and dynamic environments[14].

However, the inherent complexity of these training requirements can lead to fluctuations in cognitive load, which may affect training outcome [15] s. Current training programs for drone operation in construction often prioritize the development of technical skills, such as basic navigation and task-specific maneuvers [16]. While these foundational competencies are essential, such programs frequently place less emphasis on the cognitive challenges that operators face during the training process. Cognitive fluctuations are common when operators process complex information, multitask, and make real-time decisions, which, if unmanaged, may compromise their ability to make decisions and execute tasks effectively [17]. These limitations highlight the necessity for more advanced, adaptive training systems that not only equip operators with technical proficiency but also enhance their capacity to navigate the complexities and cognitive demands of drone operation in dynamic and unpredictable construction environments.

3 Impact of Cognitive Load on Training for Enhanced Drone Operation

Cognitive load, defined as the mental effort required to process information and perform tasks, plays an important role in influencing the efficiency and accuracy of drone operators, particularly within the dynamic and high-stakes environment of construction [19] . High cognitive load refers to a state where the mental demands of a task exceed an individual's capacity to process information effectively, leading to reduced performance and increased likelihood of errors [18]. Drone operators often need to process complex spatial, technical, and safety-related information in real time, which can amplify cognitive demands [6]. In construction settings, operators often navigate intricate and constantly changing sites, execute precise maneuvers, and respond to unforeseen challenges such as equipment malfunctions, changing environmental conditions, or sudden safety hazards [15]. Excessive cognitive load has been observed during drone operations, where it negatively impacts human performance by inducing mental fatigue, impairing situational awareness, and compromising decision-making processes [19]. Mental overload can hinder the operator's ability to process critical information, leading to reduced efficiency, operational delays, and increased risks of accidents or safety violations. As construction projects increasingly rely on drones for tasks such as surveying, monitoring, and inspection, understanding and mitigating cognitive load becomes essential for enhancing overall system performance and safety.

However, despite its importance, existing literature on drone operation training for construction lacks a comprehensive understanding of how cognitive load influences learning outcomes and task performance [4]. Most current training programs overlook the dynamic variations in cognitive load experienced by users during drone interaction training, failing to account for individual differences and task complexity. This generic training methodology risks overloading operators with excessive cognitive demands, potentially reducing training effectiveness, impairing task performance, and increasing the likelihood of operational errors [20]. Such an approach fails to prepare operators for the cognitive demands posed by real-world construction scenarios, where task complexity and situational variability are significant.

To address this gap, there is an urgent need for an adaptive training environment that dynamically adjusts task complexity based on the trainee's cognitive load. By incorporating real-time cognitive load assessment into training frameworks, task difficulty can be tailored to individual capabilities, fostering optimal learning conditions. Adaptive training has the potential to enhance learning retention, improve task performance, and better prepare operators to handle the cognitive challenges of drone operation in construction. Such a system would ensure that trainees are neither overwhelmed nor insufficiently challenged, thus promoting a balanced cognitive load that facilitates skill acquisition and long-term proficiency.

4 Method: Adaptive Human-Drone Training Platform Based on Cognitive Load For Construction Workers

This study designed and implemented an LSTM-driven adaptive training system for drone operation in a VR environment (Figure 1). Physiological signals for cognitive load assessment are processed using a preprocessing pipeline to enhance signal quality and consistency. The pre-processed physiological data is then fed into the LSTM-based adaptive training system for cognitive load prediction. Finally, the adaptive system is integrated into the VR-based training program to provide users with a dynamic and immersive simulated training environment.

4.1 Physiological signals for cognitive load assessment and data preprocessing

To assess cognitive load during training, this study utilizes two widely recognized physiological signals: heart rate variability (HRV) and galvanic skin response (GSR) [15], [21]. HRV, derived from photoplethysmography (PPG) [22], measures the variation in intervals between consecutive heartbeats, with low HRV indicating a potential state of high cognitive load. GSR, obtained from electrodermal activity (EDA), indicates changes in skin conductivity driven by sweat gland activity, with higher GSR values often associated with emotional arousal or stress. These physiological signals are continuously recorded during the training process to provide an objective assessment of the user's cognitive load. The collected data undergoes preprocessing to standardize and smooth the signals, ensuring consistency and reliability. PPG data were filtered using a fourth-order Chebyshev II filter with a passband range of 0.5–5 Hz and a stopband attenuation of 30 dB to minimize motion artifacts while retaining physiologically relevant HRV components. To align sampling frequencies across signals, EDA data were upsampled using linear interpolation to match the PPG data. Subsequently, EDA signals were processed with a third-order Butterworth low-pass filter with a cutoff frequency of 0.5 Hz.

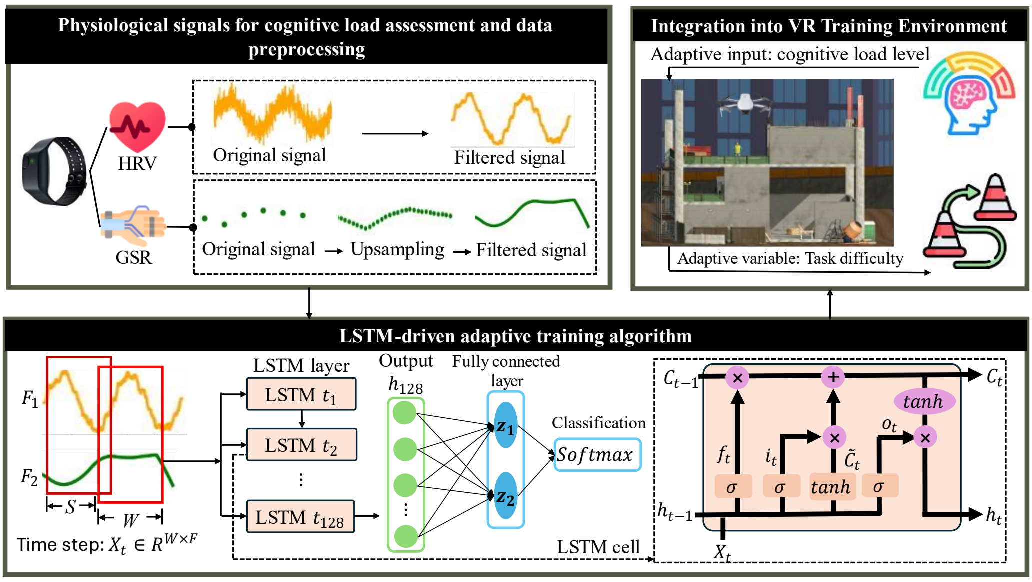

Figure 1. Overview of LSTM-driven adaptive VR training system

4.2 LSTM-driven adaptive training algorithm

The LSTM-driven adaptive training system is designed to dynamically adjust training tasks in real time based on cognitive load predictions. The goal is to maintain users within an optimal cognitive load range, balancing task difficulty and cognitive engagement for effective learning outcomes. The system is underpinned by an LSTM-based cognitive load prediction model, which processes sequential physiological signals to predict cognitive load levels. LSTM networks are particularly suitable for this task due to their ability to capture long-term temporal dependencies while selectively retaining or forgetting information through gating mechanisms.

To train the LSTM model, ground truth cognitive load labels were established by engaging. participants in tasks of systematically increasing complexity. Physiological signals, including HRV derived from PPG and GSR from EDA, were continuously recorded. Ground truth labels were determined using the NASA-TLX, a validated subjective workload assessment tool. Participants rated their perceived workload and aggregated the score into composite scores S_i , normalized as $S_i^{norm} = \frac{S_i - S_{min}}{S_{max} - S_{min}}$, where S_{min} and S_{max} are the dataset's minimum and maximum scores. The normalized scores were discretized into two cognitive load categories, "low" and "high," to serve as the ground truth labels for cognitive load classification.

Pre-processed HRV and GSR data were segmented into 10-second sliding windows with a 3-second update interval for cognitive load monitoring. The data were organized into a feature matrix $X \in R^{W \times F}$, where W is the sequence length and F is the feature dimension. The feature matrix was used as input to the LSTM-driven adaptive algorithm network. The hidden layer followed by the input layer contains 128 units. Each hidden unit processes the input sequence X by maintaining a cell state c_t and producing a hidden state h_t at each time step t. The dynamics of the LSTM are governed by its gating mechanisms, including the input gate i_t, forget gate f_t, output gate o_t, and the candidate cell state $\tilde{c_t}$. These are computed as follows [23]

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (1)$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (2)$$
$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (3)$$
$$\tilde{c}_t = \tanh\,(W_c[h_{t-1}, x_t] + b_c) \quad (4)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (5)$$
$$h_t = o_t \odot \tanh\,(c_t) \quad (6)$$

where W_f, W_i, W_o, W_c and b_f, b_i, b_o, b_c are the weight matrices and biases for the respective gates, σ represents the sigmoid activation function, $tanh$is the hyperbolic tangent function, and $\odot$ denotes the element-wise multiplication. The final hidden state h_{128}, capturing the temporal dependencies in the input sequence, is passed through a fully connected dense layer where a linear transformation is applied, given by $z = W_z h_{128} + b_z$, where W_z and b_z are the weight matrix and bias for the dense layer, and $z = [z_1, z_2, z_3]$ represents the outputs corresponding to each class. Subsequently, the output z is passed through a softmax activation function to predict the probability distribution over cognitive load levels $\hat{y} = \frac{e^{z_k}}{\sum_{i=1}^{C} e^{z_i}}, k = 1,2,3$, where $\hat{y}$ is the probability distribution over the cognitive load classes, and C corresponds to the number of cognitive load classes.

4.3 Integration into VR Training Environment

A virtual construction environment was developed to simulate realistic and dynamic construction site conditions, providing a platform for users to learn and practice drone operation. The environment was designed to replicate the complexities of high-rise construction sites, incorporating detailed architectural structures such as multi-level buildings, scaffolding, and construction equipment. Dynamic objects, including moving machines such as cranes, excavators, and forklifts, were programmed to operate autonomously, simulating real-time activities. Additionally, virtual workers were included, designed to mimic human movements and interactions within the construction site, creating a realistic sense of activity and unpredictability. To further enhance the fidelity of the environment, Rigidbody components are added to objects and collision detection was incorporated for drone collision error detection. A dual-view setup, featuring both a drone monitor and a drone's first-person view, is provided to enhance situational awareness and support precise navigation.

The LSTM-driven adaptive training system was integrated into the virtual construction environment to adjust task difficulty based on real-time cognitive load predictions. As cognitive load levels fluctuate, the system dynamically modifies elements such as drone flight paths (the number of waypoints n and the distance between waypoints d) and the behaviour of dynamic obstacles (the velocity of dynamic obstacles $v_j(t)$, and their trajectory complexity $r_j(t)$).

When a high cognitive load is detected ($\hat{y} = 3$), the system adjusts to prevent cognitive overload and enhance learning efficiency. Task complexity is reduced by simplifying drone flight paths (reducing n and increasing d), minimizing the number and movement speed of dynamic obstacles $v_j(t)$, and decreasing their trajectory complexity $r_j(t)$. Additionally, the system provides step-by-step guidance or visual cues to assist in task execution. If high cognitive load persists, short rest intervals are introduced to allow cognitive recovery before resuming training. Conversely, when a low cognitive load is detected ($\hat{y} = 1$), the system gradually increases task difficulty to ensure continued engagement and skill development. This is achieved by introducing more intricate drone flight paths (increasing n and decreasing d), introducing Gaussian noise to the velocity of dynamic obstacles ($v_j(t) \sim v_j(t) + N(0, \sigma^2)$), and selecting more complex trajectories $r_j(t)$ that simulate real-world challenges such as wind disturbances. For moderate cognitive load ($\hat{y} = 2$), the system evaluates task completion time (T) as an additional parameter. If $T > T_{threshold}$, task difficulty remains unchanged to allow further adaptation. If $T < T_{threshold}$, task complexity is incrementally increased to maintain an optimal level of challenge without inducing excessive cognitive strain.

5 Case Study: Evaluating the Effectiveness of Cognitive-Based Adaptive VR Training for Construction Worker-Drone Interaction

The experiment was designed to evaluate the effectiveness of the LSTM-driven adaptive training system for drone operation in a VR environment. The virtual environment was developed using Unity and code with Visual Studio with C# and deployed on the SteamVR platform, providing a dynamic and immersive training scenario. Physiological signals including HRV and GSR were measured using the Empatica E4 wristband. An IRB-approved study was conducted, with all participants providing informed consent before data collection. 20 Participants were divided into two groups: one group trained with the adaptive system, while the other followed a non-adaptive VR training protocol for comparison. Each participant underwent multiple training sessions consisting of tasks with systematically varying levels of difficulty. For the adaptive training group (ATG), the task difficulty was dynamically adjusted in real time based on cognitive load predictions generated by the LSTM model. In contrast, the non-adaptive training group (NATG) followed a fixed sequence of tasks with predetermined difficulty levels. During the training sessions, physiological signals, including HRV and GSR of ATG, were continuously recorded to monitor cognitive load. The adaptive system used these signals to adjust task parameters dynamically, aiming to maintain participants within an optimal cognitive load range.

Performance metrics were evaluated using both cognitive load prediction accuracy and task performance indicators. To assess the accuracy of the LSTM-based cognitive load prediction model, an initial validation study was conducted in which participants completed a series of training sessions with progressively increasing difficulty levels. After each session, participants provided self-reported ratings of their perceived cognitive load using the NASA Task Load Index (NASA-TLX), a widely recognized tool for workload assessment. These self-assessments provided a baseline for comparing the model's predictions.

To evaluate the effectiveness of the adaptive training system, pre- and post-training assessments measured task completion times as an indicator of operational efficiency. Task completion time was chosen as an objective metric to quantify the training's impact and facilitate a comparative analysis between adaptive and standard training methodologies. By integrating cognitive load prediction accuracy with performance improvements, the experiment aimed to validate the hypothesis that adaptive training not only enhances learning outcomes but also significantly improves task efficiency.

6 Results

6.1 Accuracy of the LSTM Model

The LSTM-based cognitive load prediction model demonstrated high accuracy in distinguishing between the three cognitive load levels, achieving an overall accuracy of 92%. Key performance metrics, including precision, recall, and F1-score for each class, are summarized in Table 1. It highlights that the model achieved perfect precision, recall, and F1-score for Class 1. Similarly, Class 3 demonstrated strong performance with an F1-score of 0.92. However, the recall for Class 2 was slightly lower at 0.78, indicating minor misclassification challenges for moderate cognitive load levels.

Table 1 Key Metrics for Cognitive Load Prediction

	Class 1	Class 2	Class 3
Precision	1.00	1.00	0.85
Recall	1.00	0.78	1.00
F1-Score	1.00	0.88	0.92

Figure 2 presents a confusion matrix heatmap, where the color intensity corresponds to the recall percentage for each class, normalized by row totals. Darker shades highlight higher recall values, emphasizing areas of strong predictive accuracy, while lighter shades indicate potential misclassifications or areas requiring further evaluation. The cell annotations display the absolute counts of predicted and actual classifications, providing a detailed overview of model performance.

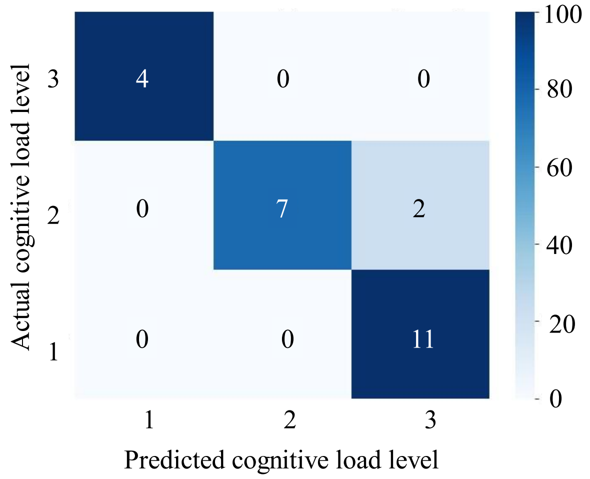

Figure 2. Cognitive Load Prediction Accuracy of LSTM-Based Adaptive Training System

6.2 Task Completion Time

Participants demonstrated significant improvements in task performance following training as Figure 3 shows. In the ATG group, the pre-training task completion time was 266.8 ± 27.5 seconds (mean ± SD), while the post-training time was reduced to 81.6 ± 11.5 seconds. This represents an average reduction of 69.4% in task completion time compared to the pre-training baseline. Similarly, in the NATG group, the pre-training task completion time was 262.1 ± 38.7 seconds, and the post-training time decreased to 110.0 ± 34.0 seconds, reflecting an average reduction of 58%. Furthermore, participants in the ATG group outperformed those in the NATG group, completing tasks 25.8% faster on average during the post-training assessments. These results highlight the effectiveness of the adaptive training system in enhancing task performance and improving operational efficiency by reducing task completion time and maintaining participants within an optimal cognitive load range during training.

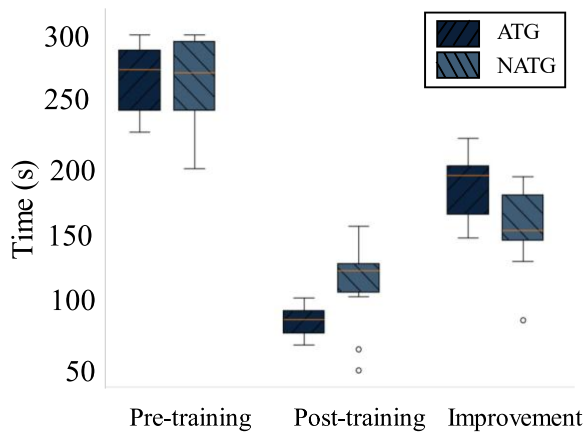

Figure 3. Task Completion Time for ATG and NATG

7 Conclusion

This research successfully developed a cognitive load-based adaptive training system to enhance drone operation training for construction workers. By leveraging physiological indicators, specifically HRV and GSR, the system effectively monitored user's cognitive load and dynamically adjusted training complexity through a LSTM neural network. The adaptive training system significantly outperformed traditional non-adaptive training methods, with participants using the adaptive system completing tasks 69.9% faster compared to their pre-training performance, while the non-adaptive group saw a 58.1% reduction in task completion time. Additionally, the LSTM-based cognitive load prediction model achieved an impressive 92% accuracy, demonstrating its reliability in assessing cognitive states.

The system's ability to adjust training complexity in real-time ensured that trainees were neither overwhelmed nor under-stimulated, leading to a more engaging and efficient learning experience that fostered better skill acquisition. Additionally, this dynamic approach inherently exposes trainees to varying levels of cognitive demands, helping them develop the ability to operate under pressure and adapt to unpredictable conditions. By adjusting task complexity and introducing real-time environmental variability, the training framework fosters resilience and stress management skills, better preparing workers for real-world drone operations. This personalized approach mitigates cognitive fatigue and improves overall task performance, contributing to more effective human-drone collaboration.

This study has certain limitations that present opportunities for future research. The current cognitive load assessment relies solely on HRV and GSR, which may not fully capture all aspects of cognitive strain. Future research will integrate additional physiological indicators, such as electroencephalography (EEG) and eye-tracking data, to enhance prediction accuracy and system adaptability. Additionally, while the LSTM-based model demonstrated strong predictive accuracy, its reliance on sequential dependencies may introduce latency in responding to sudden cognitive state changes, potentially compromising the real-time adaptability of the training system. Future research exploring hybrid architectures, such as integrating LSTM with attention mechanisms, could mitigate these challenges by enhancing responsiveness and robustness in highly dynamic construction training environments.

By integrating real-time physiological monitoring with adaptive learning algorithms, this study addresses critical gaps in existing training methodologies for drone operation in construction. The proposed system not only improves task performance and operational efficiency but also ensures that training is tailored to the cognitive capacities of individual workers. These advancements pave the way for more resilient and effective human-drone collaborations, ultimately contributing to safer and more productive construction practices.

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