Solar Energy Systems Design using Immersive Virtual Reality: A Multi-Modal Learning Approach

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Abstract

As the demand for renewable energy sources continues to increase, solar energy is becoming an increasingly popular option. Therefore, effective training in solar energy system design and operation is crucial to ensure the successful implementation of solar energy technology. To make this training accessible to a wide range of people from different backgrounds, it is important to develop effective and engaging training methods. Immersive virtual reality (VR) has emerged as a promising tool for enhancing solar energy training and education. In this paper, we present a unique approach to evaluating the effectiveness of an immersive VR experience for solar energy systems design training, using a multi-module approach and a detailed analysis of user engagement. To better understand the effectiveness of this VR experience, we divided our experiment into several scenes and employed a range of sensors, including eye-tracking and wireless wearable sensors, to accurately assess users' engagement and performance in each scene. Our results demonstrate that the immersive VR experience was effective in improving users' understanding of solar energy systems design and their ability to perform complex tasks. Moreover, by using sensors to measure user engagement, we identified specific areas that required improvement and provide insights for enhancing the design of future VR training experiences for solar energy systems design. Our study highlights the potential of immersive VR as a tool for enhancing solar energy training and education, with implications for both research and practice.

Solar Energy Systems Design using Immersive Virtual Reality: A Multi-Modal Learning Approach

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***Abstract*—As the demand for renewable energy sources continues to increase, solar energy is becoming an increasingly popular option. Therefore, effective training in solar energy system design and operation is crucial to ensure the successful implementation of solar energy technology. To make this training accessible to a wide range of people from different backgrounds, it is important to develop effective and engaging training methods. Immersive virtual reality (VR) has emerged as a promising tool for enhancing solar energy training and education. In this paper, we present a unique approach to evaluating the effectiveness of an immersive VR experience for solar energy systems design training, using a multi-module approach and a detailed analysis of user engagement. To better understand the effectiveness of this VR experience, we divided our experiment into several scenes and employed a range of sensors, including eye-tracking and wireless wearable sensors, to accurately assess users' engagement and performance in each scene. Our results demonstrate that the immersive VR experience was effective in improving users' understanding of solar energy systems design and their ability to perform complex tasks. Moreover, by using sensors to measure user engagement, we identified specific areas that required improvement and provide insights for enhancing the design of future VR training experiences for solar energy systems design. Our study highlights the potential of immersive VR as a tool for enhancing solar energy training and education, with implications for both research and practice.**

***Index Terms*—Virtual reality, eye tracking, vital signs, engagement level.**

I. Introduction

Addressing some of the world's most pressing environmental challenges demands a paradigm shift in the way we design and develop renewable energy systems. Conventional methods rely on experts creating designs on 2D flat screens using outdated CAD models, often at a great distance from the actual site or community. This separation requires designers to painstakingly adapt images of the actual site to the flat screens on which these designs are being developed. In particular, our vision is to revolutionize solar energy system design and education by allowing users to experience the actual site as if they were physically present. This sense of presence frequently leads to higher design performance and deeper comprehension. Indeed, humans possess an innate ability to instantly understand an environment simply by being present in it. Presence allows us to confidently form hypotheses, plan actions, and make discoveries. Visualization tools, with their interactive and representational capabilities, can further facilitate higher levels of engagement, ultimately enhancing learning and understanding of the presented information.

Virtual reality (VR) is one of the most promising visualization tools in education, training, and instructional design, offering users an innovative immersive experience. Researchers are increasingly exploring and evaluating this immersive environment to enhance user experience, comprehension of content, decision-making, and problem-solving [1]. Maintaining positive psychological states such as motivation and engagement is crucial to prevent boredom and loss of focus after repeated exposure [2]. The latest VR headsets, including HTC Vive and Oculus Rift, deliver high levels of immersion to users [3] [4]. This immersion influences the level of presence, which is the sensation of being in the virtual world [5]. Jennett *et al.* in [6] discussed the three core concepts frequently used to characterize engagement experiences: flow, cognitive absorption, and presence.

Numerous VR studies examine the relationship between users' performance and their sense of presence in the virtual reality environment, particularly in the context of education and training [7], [8]. In fact, several studies in the literature have employed virtual reality technology in solar energy education and training. For example, Lopez *et al.* in [9] present a study aiming to foster students' self-learning in the installation of a photovoltaic power plant. Similarly, P. Abichandani *et al.* in [10] introduce a novel virtual reality educational system teaching students the fundamentals of PV cells, solar modules, and various PV array installation configurations. Alqallaf *et al.* [11] present a VR game-based approach for teaching basic solar energy system design concepts to higher education students.

In recent human-computer interaction studies, measuring user experience (UX) primarily relies on self-reported data, questionnaires, and user performance. However, questionnaires as self-assessment methods face two main challenges: the potential for misinterpretation and misunderstanding of the items' meanings, and the risk of eliciting stereotypical responses [12]. Current research advocates for the integration of physiological measures into immersive virtual reality applications and experiments, as they can significantly complement self-report data when estimating users' emotions and stress levels [13]. Furthermore, combining both objective and subjective methods leads to more reliable results [12].

Many contemporary theories of emotion view the autonomic nervous system's (ANS) activity as a significant contributor to emotional responses [14]. Bio-signals, such as electrocardiography, electroencephalography, and blood pressure monitoring, can provide objective data. Engagement is associated with physiological changes, including increased heart rate, sweating, tensed muscles, and rapid breathing [15]. The degree of engagement affects the autonomic nervous system, which in turn influences physiological changes in the body [15]. McNeal *et al.* in [16] presented a study using galvanic skin response (GSR) to measure students' engagement levels in an Introductory Environmental Geology Course. Similarly, Lee *et al.* in [17] employed electrodermal activity (EDA) measurements to gauge cognitive engagement in Maker learning activities. Darnell and Krieg utilized heart rate measurements via wristwatch monitors to assess cognitive engagement among medical school students [18].

As levels of engagement influence the autonomic nervous system and are associated with physiological changes in the body, these responses can be expressed through specific bio-signals, including signals reflecting learner engagement indices in class. By combining physiological parameters such as heart rate, breathing rate, skin conductance, and other sensor data, a comprehensive understanding of users' emotional behavior can be obtained.

II. Eye Tracking in VR

Virtual reality has opened new avenues for integrating implicit measures such as eye tracking, which can reveal unconscious processes and provide valuable insights into users' behavior and attention distribution in various sectors of education [19]. The assessment of eye tracking data in virtual reality environments creates novel research opportunities to understand users' visual attention [20] and cognition [21], especially with the advent of head-mounted displays (HMD) featuring built-in eye tracking capabilities [22].

A crucial aspect of evaluating cognitive function lies in the analysis of eye tracking parameters, as they can more accurately reflect human mental states compared to other bio-signals [23]. The main eye movement measures obtainable through eye tracking are fixation and saccades [24]. By analyzing these data, user experience researchers can gauge users' engagement levels by interpreting the number of eye fixations and average fixation duration [25], [26].

In addition to eye movements, pupil dilation serves as a psychophysiological arousal indicator, regulated by autonomic nervous system activity [27], [28], [29]. Research has established correlations between pupil dilation, task engagement, and task difficulty [30], [31], [32].

Moreover, eye blinking rates are influenced by variables such as cognition, task engagement, and exhaustion [33]. Various studies have demonstrated a relationship between blinking rate and task difficulty or engagement [34], [35], [36].

The Cognitive Load Theory (CLT) underscores the importance of avoiding overloading working memory to maximize learning [37], [38], [39]. In this context, eye-tracking variables have been employed in the literature for measuring cognitive load [40].

To summarize, eye tracking and vital sign data are essential techniques for observing user behavior in virtual reality environments. By seamlessly interconnecting and analyzing these data, researchers can obtain valuable insights to enhance instructional design in immersive applications, ultimately improving user experience and learning outcomes.

III. Approach and Hypotheses

In our previous paper [41], we compared learner engagement levels in a 2D application and a 3D immersive virtual reality application for designing solar energy systems. We estimated learner vital signs using a non-invasive radar sensor and validated the data with self-reported questionnaires. Our study confirmed our hypothesis that a 3D virtual reality application leads to higher engagement levels than a 2D application. Figure 1 illustrates the heart rate of a participant who designed a solar energy system using both 2D and 3D applications.

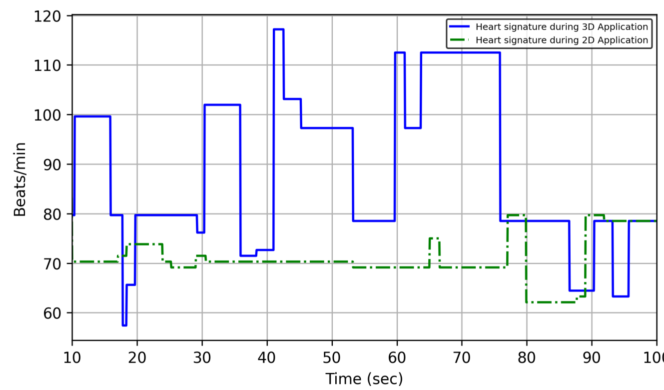

Fig. 1: Comparison of a participant's heart rate from Radar sensor during 2D application and 3D immersive virtual reality environment.

In the present study, our goal is to measure learner engagement levels while designing a solar energy system in our novel 3D immersive environment, analyzing biofeedback and eye-tracking data. We aim to compare biofeedback reflecting engagement levels within the VR experience across different scenes. Identifying areas of low learner engagement can guide modifications to the application's design, thereby increasing learner attention and focus. Moreover, our approach to collecting data offers the key advantages of being wireless, wearable and unobtrusive compared to other methods of measuring vital signs and eye-tracking data.

Most importantly, we aim to extend our understanding of learner engagement and experience in the 3D immersive virtual reality environment by focusing on specific scenes within the application and analyzing eye-tracking and biofeedback data. Therefore, we propose the following three research questions (RQ's) and hypotheses (H):

1) ***RQ1***: How do users' engagement levels differ across various scenes within the 3D immersive virtual reality environment when designing solar energy systems?
   - ***H1***: Users' engagement levels vary across different scenes in the 3D immersive virtual reality envi-

Fig. 2: The Dale's cone, the cone of experience, elucidates different categories in experience and shows the effectiveness of learning by doing in retaining more information than learning by hearing, seeing and observing.

ronment, with certain scenes eliciting higher engagement levels than others during the solar energy system design process.

2) ***RQ2***: How do eye-tracking data and biofeedback correlate with user experience (UX) and engagement levels in the 3D immersive virtual reality environment?
   - ***H2***: Eye-tracking data and biofeedback effectively reflect users' UX and engagement levels, with increased fixation durations and lower blink rates indicating higher engagement in the 3D immersive virtual reality environment.
3) ***RQ3***: To what extent do modifications in the 3D immersive virtual reality environment, informed by biofeedback and eye-tracking data, improve user engagement and focus in designing solar energy systems?
   - ***H3***: Modifications to the 3D immersive virtual reality environment, based on biofeedback and eye-tracking data, lead to significant improvements in user engagement and focus in designing solar energy systems.

In accordance with Dale's cone theory [42], which structures learning experiences, we chose to focus on active and passive learning through hands-on experiences, since these are situated at the base of the cone, as shown from Figure 2. This decision stems from the fact that teaching sustainable energy subjects typically relies on a theoretical approach, which may not provide the most effective learning experience [43].

IV. Methodology

As mentioned earlier, traditional evaluation methods such as quizzes, multiple-choice questions and self-reported questionnaires may not always provide the most accurate assessment of VR experiences. Instead, researchers should consider using operational, protocol, and behavioral measurements that are combined with neurocognitive methods to evaluate user experience for a more comprehensive evaluation [44] [45] [46] [47]. Operational measurements often assess a learner's ability to correctly operate equipment or machinery, while protocol measurements evaluate whether the learner adheres to a prescribed process for a specific job task. In contrast, behavioral measurements examine whether the learner exhibits the desired behavior in a given situation. Given that solar energy systems design involves a set of procedures and best practices (a protocol) that designers must follow, we developed a methodology to evaluate the effectiveness of our VR experience.

To gain a deeper understanding of learner engagement, we divided the VR experience into distinct scenes. Our objective was to observe participants as they interacted with the VR experience, identifying the aspects that captured their interest, the elements they grasped quickly, the parts they wanted to explore further and the areas they found challenging. We also aimed to pinpoint unclear rules and mechanics that were not yet fully developed within our VR experience. By analyzing participants' interactions, we sought to determine which mechanics were enjoyable and which ones needed fine-tuning to balance the experience and guide users towards the intended learning objectives at an appropriate pace. Our motivation behind this approach was to gain valuable insights into the design of the VR experience and refine it accordingly. To collect real-time data during this process, we used physiological sensors as an additional evaluation tool.

In our methodology, we divided the VR experience into three main scenes, each corresponding to a crucial task in a typical solar energy system design project. These tasks are vital for ensuring the efficiency, functionality and optimal performance of the solar energy system. Here is a summary of the tasks associated with each scene:

Scene 1: Site Selection - Users begin by choosing a location for installing the solar energy system. Accurate site selection is crucial for maximizing solar energy production, as it accounts for factors such as available sunlight, local weather conditions and physical constraints.

Scene 2: Power Room - In this scene, users explore the power room, where they can interact with the essential system components, such as batteries, inverters and charge controllers. Users can use the VR controllers to grab and install the components on a stand. Familiarizing themselves with these components and understanding their roles is essential for designing a functional solar energy system that meets energy production and storage requirements.

Scene 3: Solar Panel Installation - The third scene takes users to the house's roof, where they can experiment with the arrangement of solar panels on a stand. Users can add, remove and adjust the tilt of the panels, observing the effects of these changes on the solar power output and electricity generation, as displayed by a gauge. This task is critical in the design process, as optimizing the solar panel arrangement can significantly impact the system's overall efficiency and energy production.

By incorporating these essential tasks into the VR experience, we wanted to give users gain hands-on experience and develop a comprehensive understanding of the solar energy systems design process.

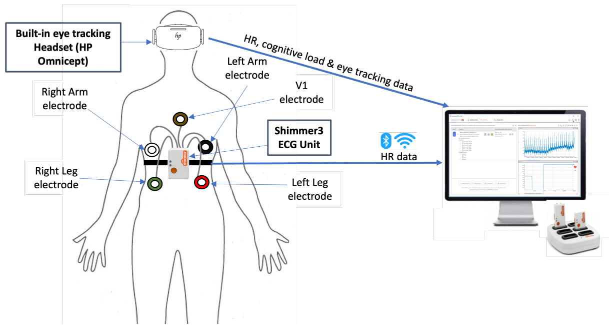

Fig. 3: Hardware setup and electrode placement: A wireless Shimmer3 ECG system employing Bluetooth and WiFi for heart rate data streaming. The Shimmer kit collected data using ConsensysPRO software. The HP Reverb G2 Omnicept has a built-in eye-tracking headset and other sensors that were used to gather participants' heart rate, cognitive load and eye-tracking data.

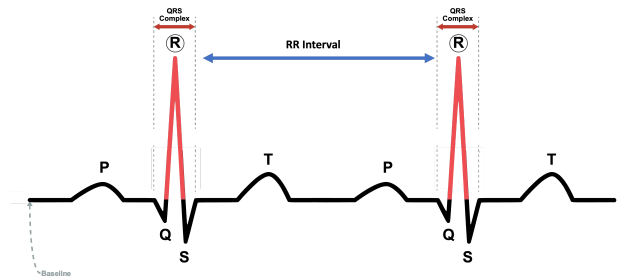

Fig. 4: ECG signals that show QRS wave for calculating heartbeats.

In the following sections we will provide a detailed account of the hardware and software used for developing and evaluating the effectiveness our VR experience.

A. Hardware

Psychophysiological signals were collected using the Shimmer Sensing Kit [48], which featured a sampling rate of 204 Hz for measuring electrocardiogram (ECG). The ECG electrodes were positioned on the chest as shown in Figure 3: Right Arm (RA), Right Leg (RL), Left Arm (LA), Left Leg (LL), and V1.

The virtual environment was displayed through the HP Reverb G2 Omnicept [49], equipped with an integrated eye-tracking system powered by Tobii. This Head Mounted Display (HMD) offers a field of view of 114 degrees, presenting the scene with a resolution of 2160×2160 pixels per eye and a combined resolution of 4320×2160 pixels. The headset also features a refresh rate of 90 Hz. Furthermore, the integrated sensors in the headset provide heart rate, cognitive load, and eye-tracking data, enabling the tracking of user engagement and the evaluation of user responses in real-time. These data also facilitate a deeper understanding of user performance and inform decision-making regarding the application's design.

B. ECG Analysis

Heartbeats are decomposed into five main waves: P, Q, R, S and T [50]. The R waves can be used from the electrocardiogram to determine the heart rate in beats per minute (BPM). This wave is a part of the QRS complex, which is the main spike shown in the ECG signals representing Ventricular depolarization. Figure 4 shows the ECG Waveform and QRS complex, which can be used to calculate the heartbeats from the ECG signals.

The Shimmer software, known as ConsensysPRO, employs an ECG-to-HR algorithm that allows users to access heart rate data from the ECG sensor. ECG signals were concurrently collected from participants via five disposable electrodes attached to their skin. Data were streamed to ConsensysPRO using Bluetooth and saved in a CSV file for each participant. Additionally, a custom script based on the HP Omnicept SDK was developed, capable of capturing heart rate, cognitive load, and eye-tracking data. These data were stored in separate files for each scene of the VR application and for each participant. At this stage, a low-pass filter was applied to the ECG signals to preserve crucial low-frequency components while attenuating high-frequency noise.

Similarly, eye-tracking data were cleaned and pre-processed using Python (3.9). Filtering the eye-tracking data from the VR headset involved utilizing a confidence level of 1, which refers to selecting only the most certain and reliable data for analysis, ensuring the analyzed data is free from errors and biases.

As the three scenes in the VR application have varying durations and are task-based, blinking and the number of fixations were normalized using the MinMaxScaler function. This transformation adjusted the values to a range between 0 and 1, facilitating data comparison across different scenes while also eliminating the effects of varying scene durations or individual characteristics.

C. Virtual Reality Setup

The experiment was conducted in a VR lab, with participants taking part voluntarily via an ethically approved consent form that was approved by our university. Initially, participants were briefed on the instructions and the purpose of the experiment. Then, they were asked for permission to place the ECG electrodes at the specified positions. Omnicept Overlay was utilized to visualize heart rate and cognitive load data concurrently. Open Broadcaster Software (OBS) was employed to record and live-stream the VR application, including the overlay screen, as shown in Figure 6-(B). Prior to starting the VR application, calibration was carried out for each participant to ensure optimal accuracy when performing the eye-tracking measurements, as depicted in Figure 5.

Moreover, the 3D application was developed using the Unity3D game engine [51], version 2020.3.25f1. C#, the programming language, was used to create the application's scripts. OpenXR was used in this application to create VR functionality such as grabbing and locomotion. The OpenXR Plugin package was used for implementing all VR-specific features. As previously mentioned, our application was divided

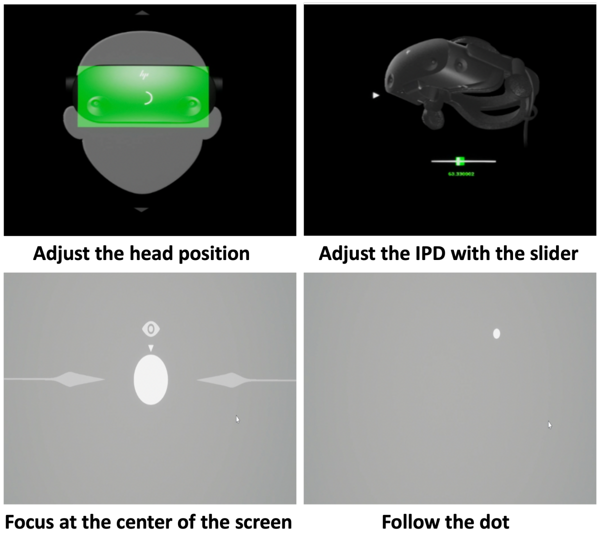

Fig. 5: Before starting the VR application, participants performed a calibration for the eye-tracking to ensure optimal data accuracy. The procedure involved (a) adjusting the head position, followed by (b) setting the interpupillary distance (IPD) using the slider. Subsequently, (c) participants focused on the center of the screen, and finally, (d) they were instructed to follow the dot.

into the three main scenes shown in figure 7. Furthermore, we implemented the VR application on a Lenovo laptop with Windows 11 having a 64-bit operating system and an Intel Core i7 with an NVIDIA GeForce RTX 3070 graphics card.

D. Finding the Average Brightness for the VR Scenes

Numerous studies have reported that eye-tracking data, particularly pupil dilation, can be influenced by the luminance of the environment. As a result, we analyzed the brightness levels of the three scenes in the VR application. We recorded a 30-second video for each scene and used Python code with the OpenCV video processing library to extract frames from the videos and convert them to grayscale. Subsequently, we calculated the lightness value for each frame by determining the mean pixel value of the grayscale frame, summing up all pixel values, and dividing by the total pixel count. Finally, we computed the average lightness values for the entire video by adding all the lightness values and dividing by the total number of frames.

E. Self-Report Questionnaire Design

Participants took part in the project voluntarily via ethically approved consent using anonymous and confidential online self-report questionnaires after experiencing the virtual reality application and collecting the vital data using the headset and the ECG sensor. They were also informed that they were able to withdraw their participation from the project at any time. The questionnaire consists of fourteen questions designed to measure the engagement and immersion level of the participants in general and for each scene. The first question was whether the participants had a previous experience with virtual reality. The second question asked participants to rate how easy the application was from 1 to 5, where 1 (Extremely Difficult) and 5 (Extremely easy). The third question was about asking the participants if they felt engaged in the virtual environment or not. The fourth question enabled the participants to select the scene they felt more engaged in, in front of the house, the power room, or the roof. In questions 5, 6 and 7, participants rated their engagement level in each scene from 1 to 5, where 5 is the highest engagement level. Questions 8 to 14 were taken from the unified questionnaire on user experience (UX) in an immersive virtual environment(IVEQ) proposed by [12] related to measuring engagement and immersion sub-scales.

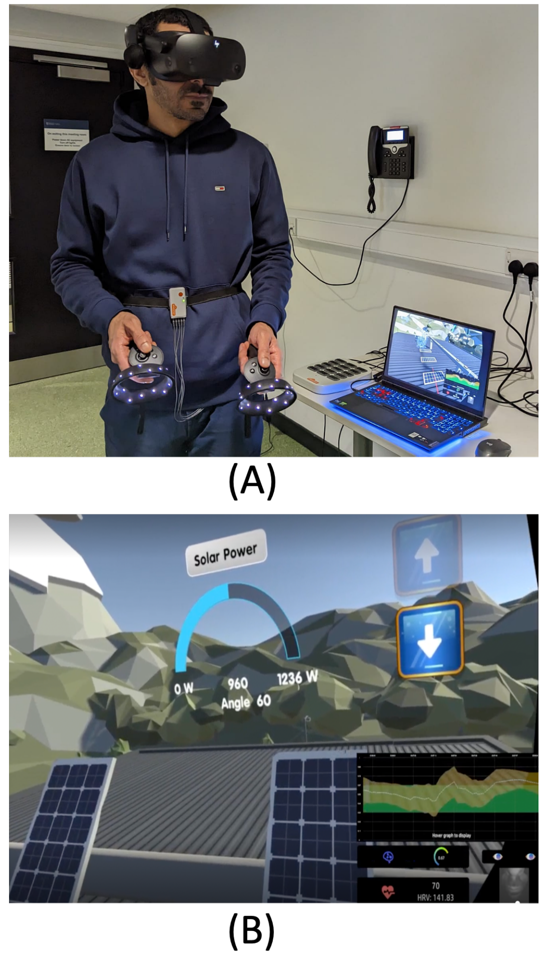

Fig. 6: The experiment setup. (A) the user is wearing the ECG sensor and the HP headset to perform the VR application. At the same time, the application was live-streaming and recorded on a laptop. (B) The screen of the OBS studio where the overlay app was transparently appeared for casting the heart rate and cognitive load data from the HP headset.

F. Participants

A total of 27 students from the University of Glasgow volunteered to take part in our experiment. These participants

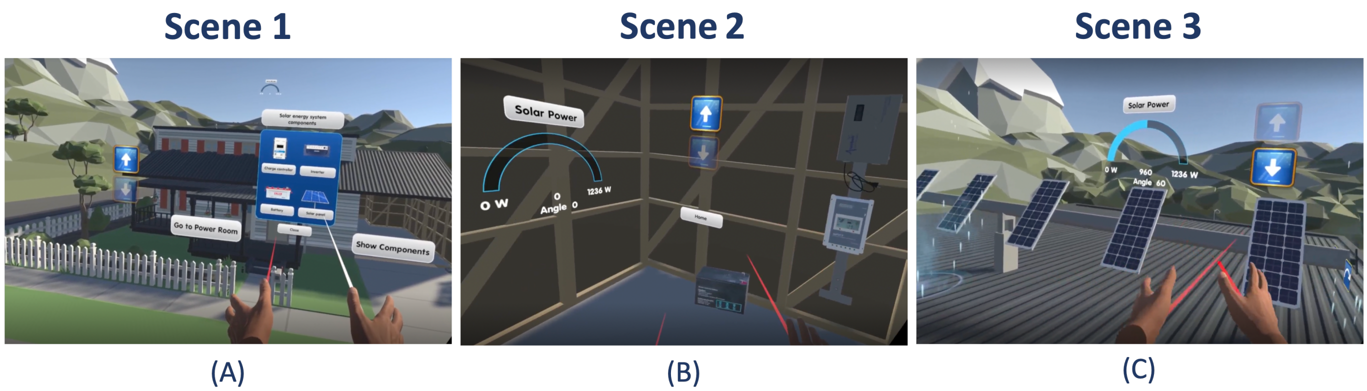

Fig. 7: The three main scenes in the VR application: (A) Site Selection, where users are positioned in front of the house, learning about system components before installing the solar energy system. (B) The Power Room, where users can grab and place the system components on the designated stand. (C) Solar Power Installation, where users can add, remove, and adjust the angle of the stand, observing changes in the power generated from the system via the gauge chart.

included 17 males and 10 females, ranging from 25 and 42 years old. All participants were healthy and did not take medication for heart problems or mental diseases.

V. Results

A. *Self-Reported Questionnaire Results*

Participants completed self-report questionnaires that assessed their sense of immersion and engagement in each scene of the application. Out of the 27 users, 12 (44% of the participants) had previous experience with VR. On a scale of 1 to 5, with 1 being extremely difficult and 5 being extremely easy, 23 participants (85% of the population) rated the application as easy to use, selecting scores of 4 and 5. Meanwhile, 4 participants (15%) chose scores of 3 or below.

Regarding engagement in VR, 48% of participants strongly agreed that they felt engaged, 44% agreed, 4% were neutral, and 4% strongly disagreed. When asked which scene they felt most engaged in, 4% chose the front of the house scene, 30% chose the power room scene, and 67% chose the house roof scene. Figure 8 illustrates participants' responses when rating their engagement level during the three scenes.

When asked if the visual aspects of the virtual environment engaged them, 44% of participants rated the engagement as extremely high (5), 41% chose 4, and 15% chose 3. In terms of feeling compelled or motivated to move around inside the virtual environment and complete the application, 41% of participants rated this aspect as extremely high (5). Furthermore, 59% of participants rated their involvement in the virtual environment as extremely high (5).

Regarding stimulation from the virtual environment, 52% of participants selected an extremely high rating (5), while only one participant (4%) chose a neutral rating (3). As for becoming so involved in the virtual environment that they were unaware of things happening around them, 33% rated this aspect as extremely high (5) and 37% rated it as 4. When asked if they felt physically present in the virtual environment, 30% rated this aspect as 5 and 52% rated it as 4. Finally, 33% rated their involvement in the virtual environment as extremely

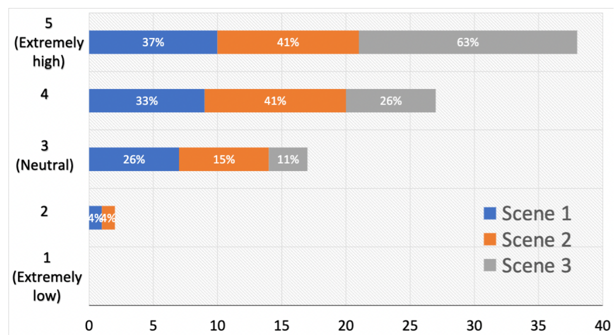

Fig. 8: Figure illustrates the participants' engagement levels during the three scenes, with 5 representing extremely high engagement and 1 representing extremely low engagement.

high (5) when it came to losing track of time, while 37% rated it as 4.

B. *Vital Signs and Eye Tracking Data*

Based on the literature, we analysed the data representing users' engagement level, such as heart rate, cognitive load, blinking rate, pupil dilation and the number of fixations. The row data from the headset is interpreted through machine learning to provide real-time insight.

1) Heart Rate: After analysing the heart rate data from the ECG sensor and the sensor from the HP headset, we found that the accuracy for the HP headset was 86.72% compared with the ECG sensor. Therefore, we decided to rely on the ECG data for analysing the heartbeat signals. Interestingly, the means of the heart rate level were almost identical in the three scenes. This suggests that there is no impact of the heart rate data in measuring the level of engagement in a VR environment.

2) Cognitive Load: As anticipated, our results show that the highest cognitive load was observed in Scene 1 due to the amount of text included in this scene. Users in the first scene had to read and comprehend the role of each component in the solar energy system. This may indicate that the cognitive

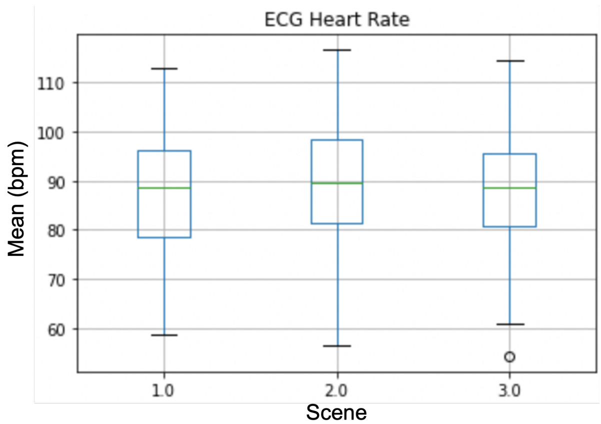

Fig. 9: The mean heart rate values during the three scenes. The finding shows that there is no significant difference in the ECG signals for the three scenes, which indicated that there is no impact of the heart rate data in measuring the level of engagement in virtual reality environment.

demands of processing textual information, particularly when learning new concepts, are higher compared to the other tasks.

Scene 2 exhibited the lowest cognitive load values, as the task involved grabbing and placing 3D objects, the system components, on a stand. This suggests that the task in Scene 2 was more intuitive and relied primarily on users' motor skills, thus requiring less cognitive effort.

Scene 3 was intermediate, as it combined interactions with 3D objects and observation of the results generated by the system. This could be interpreted as an indication that users were engaged in both cognitive processing and motor skills, balancing the overall cognitive load.

Figure 10 displays the box plot of cognitive load data across the three scenes. These findings can inform future refinements of the VR experience by optimizing the amount and presentation of information in each scene, balancing cognitive load and ensuring that users remain engaged throughout the experience.

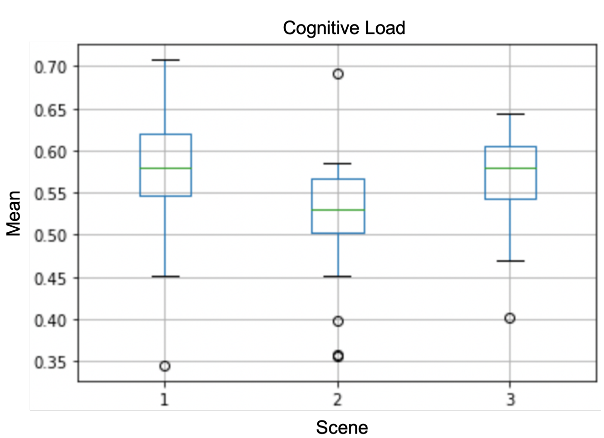

Fig. 10: The cognitive load of the users during the three scenes in the virtual reality application. The results showed that Scene 1 had the highest cognitive load while Scene 2 had the lowest.

3) Pupil Dilation: We examined the changes in pupil dilation among participants across the three scenes. Our findings show the greatest pupil dilation for participants in Scene 2, the power room. As previously mentioned, pupil size tends to decrease as the brightness of the visual environment increases. Figure 11 illustrates the noticeable difference in average brightness in Scene 2 compared to the other scenes, which led to increased pupil size for participants.

The brightness level for Scenes 1 and 3 is nearly the same, but the pupil size for participants in Scene 3 is larger than in Scene 1. This discrepancy may be attributed to the difference in the tasks' difficulty and the nature of the environment, as pupil size typically increases with a rise in mental activity and engagement level.

These results suggest that the tasks in Scene 2 and Scene 3 could have been more cognitively engaging or demanding for participants, while Scene 1, despite its textual information, may not have induced the same level of mental effort. Additionally, the variations in brightness between scenes may have influenced pupil dilation, further affecting the interpretation of cognitive load or engagement. Future iterations of the VR experience may benefit from taking these factors into account to optimize the balance between engagement, cognitive load, and visual design.

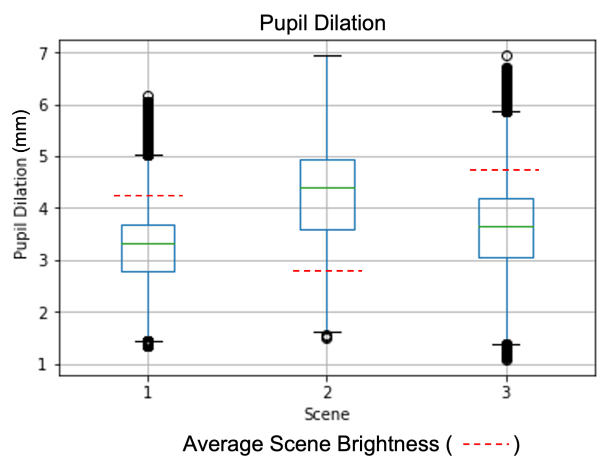

Fig. 11: The pupil dilation for the participants within the three scenes. Our results showed that the largest pupil dilation occurred in scene 2 while the smallest dilation appeared in scene 1. The red line represents the average brightness level for each scene in 30 seconds. Scene 2 had the lowest brightness level, while scenes 1 and 3 had close brightness levels.

4) Blinking Rate: Figure 12 illustrates the normalized blinking rate for participants across the three scenes. We normalized the data for the blinking rate in each scene to account for the differences in duration between them. The highest number of blinks occurred in Scene 2, followed by Scene 3 and Scene 1, respectively.

The differences in blinking rates among the scenes could suggest varying levels of cognitive load, attention, or visual engagement for the participants. A higher blinking rate in Scene 2 might indicate increased cognitive effort, possibly due to the interaction with 3D objects or the lower brightness level in that scene. Meanwhile, the lower blinking rates in Scenes 1 and 3 might be indicative of reduced cognitive load or increased focus on the tasks at hand. It is essential to consider these factors when evaluating user engagement and cognitive load in the VR experience. Further analysis of the relationship between blinking rate and other physiological or behavioral data might offer additional insights into the effectiveness of each scene in promoting learning and engagement.

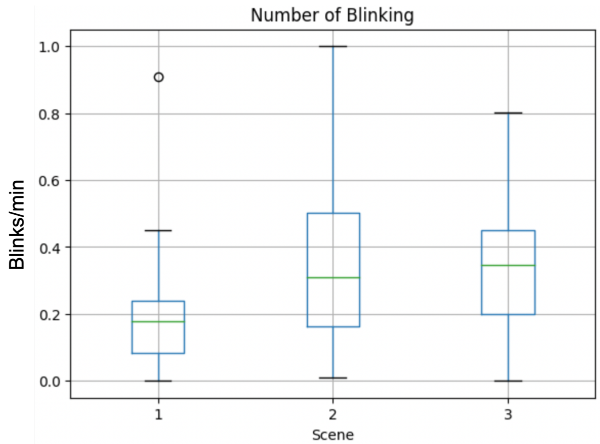

Fig. 12: The difference in blinking among the three scenes. The results showed that Scene 2 had the highest blinking rate, while Scene 1 had the lowest.

5) Number of Fixations: Figure 13 presents the number of fixations for participants during the three scenes. Our findings reveal a significant difference in the number of fixations across the scenes, with Scene 2 having the highest number of fixations.

The higher number of fixations in Scene 2 could be indicative of increased visual attention or cognitive effort, as participants may have been more focused on manipulating and placing the 3D objects in the power room. This could also suggest that Scene 2 was more engaging or required more intricate interactions, drawing the participants' gaze more frequently to various elements within the scene.

Conversely, the lower number of fixations in Scenes 1 and 3 might imply that participants found these scenes less visually demanding or cognitively challenging. However, it is essential to consider the context of the tasks and the nature of the interactions within each scene when interpreting these findings. A more detailed analysis of the spatial distribution and duration of fixations, alongside other physiological or behavioral data, could offer a deeper understanding of the participants' engagement, learning, and cognitive load during each scene in the VR experience.

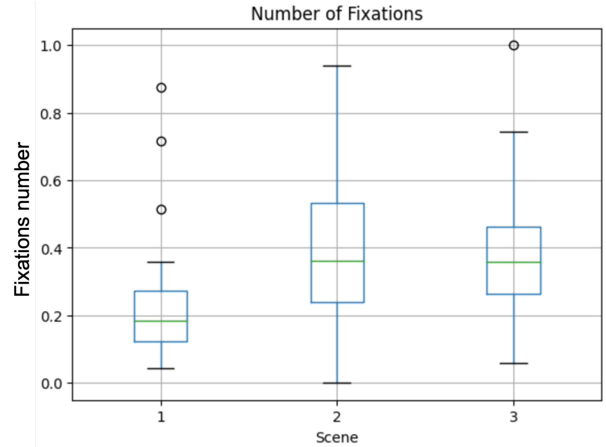

Fig. 13: The number of fixations during the three scenes. Scene 2 had the highest fixations number, while Scene 1 had the lowest.

Finally, table I provides a summary of the mean and standard deviation values for all parameters across the three scenes in the VR application.

TABLE I: Summary of the Collected Data Analysis

	Scene#	Mean	SD
Heart Rate	1	88.15	16.28
	2	88.06	16.07
	3	88.04	13.94
Cognitive Load	1	0.582	0.132
	2	0.513	0.163
	3	0.567	0.135
Pupil Dilation	1	3.260	0.717
	2	4.314	0.929
	3	3.636	0.857
Blinking Rate	1	0.20	0.18
	2	0.36	0.28
	3	0.34	0.20
Number of Fixations	1	0.24	0.20
	2	0.40	0.25
	3	0.38	0.20

VI. Discussion

Human-computer interaction innovations depend heavily on understanding users' mental states. This study investigated UX during a 3D immersive virtual environment using an HP Omnicept headset and the ECG sensor on a solar energy systems design task. We investigated whether eye tracking, heart rate and cognitive load data would be associated with increasing engagement and cognitive level in each scene of the VR application. We also formulated three RQ's and hypothesis at the start of the experiment around these areas and we will now discuss our findings related to these hypotheses.

We hypothesised that diverse emotional responses within the three scenes would have produced various attention patterns. Results from our study showed that the user experience and engagement level could be estimated by analysing eye-tracking data, as the eyes can reveal much more about a person's emotions than most people realise and are a slightly more enigmatic indicator of their emotions.

Despite the survey showing greater engagement in a specific scene, there is no difference in the heart rate data. The participants in the three scenes had almost equal heart rate levels, and there was no significant impact from the ECG signals related to the engagement level. The VR game was likely immersive and engaging for all participants during the three scenes. Our finding with the ECG sensor contradicts what was shown by the study of Murphy and Higgins in [52]. They used ECG and EEG sensors to assess user engagement in an immersive virtual reality environment. Their findings showed that the heart rate is a good indicator for measuring the users' engagement level in virtual reality.

It was hypothesised that utilising an approach that increased cognitive load when teaching a topic to students would have an adverse effect on their performance [53]. A task becomes more challenging and places a heavier intrinsic load on working memory when it has a greater number of interconnected informational components. The cognitive load in scene 1 is higher than in scenes 2 and 3. This was to be expected because participants needed to read and understand the role of the solar energy system components, as there is a lot of text in this scene.

Psychologists have long been curious about how changes in pupil size and mental activity relate to one another [54]. Also, mental activities are closely connected with problem difficulty, which affects pupil response [31] [55]. We predicted that pupil dilation would be affected by the users' engagement and performance in the VR application in different scenes. Pupil diameter is a complicated parameter in eye-tracking because it is affected by the brightness of the visual stimulation [56] and cognitive load [57]. Our results showed increased pupil dilation in scene 2, which had a lower average brightness level than in scenes 1 and 3. This was aligned with the literature that the pupil size and brightness of the visual environment are found to be inversely proportional [58]. This finding suggests the importance of considering the effect of visual brightness on pupil size while reliably measuring the user experience in virtual reality applications. Moreover, when comparing scenes 1 and 3, there is no significant difference in the average brightness level between them, but the pupil dilation in scene 3 is larger than in scene 1. This indicated the relationship between pupil dilation and task difficulty [59], increasing the level of interest and arousal [60] and users' attention [61].

As we mentioned earlier, scenes 1 and scene 3 have different physical efforts. In scene 1, users read and understand the role of the solar energy system components by clicking on buttons and demonstrating the information. While in scene 3, users interact more with the 3D objects as they grab and place the solar panels and try different situations of the system. This physical activity has an impact on pupil dilation. Our results revealed that the size of the pupil increased in response to physical exertion like one of a previous study indicated that pupil size increased during physical effort [62].

Higher blink rates are frequently observed in insight problem-solving situations and creativity performance [63] [64]. However, a previous study observed the relationship between the blinking rate and visual attention [34]. The result of this study indicated that the blinking rate increases when visual attention is engaging and vice versa. Our findings indicated the relation between the blinking rate and task difficulty. The blinking rate in scene 1 was lower than in scenes 2 and 3, as the task in scene 1 was very easy to perform. This aligned with the finding from the study by Tanaka and Yamaoka [36], which shows that the blinking rate with the difficult task was higher than for the easy task. In addition, the blinking rate is affected by the nature of the task. Users experienced different types of tasks during the three scenes, which produced different levels of blinking rates. Also, endogenous blinks are reduced when a task demands more concentration [65], which was clearly obvious with the blinking rate in scene 1. The amount of text in scene 1 reduced the blinking rate of the participants as they had to be focused on comprehending the presented information. This finding matches the literature that indicated that the blinking rate reduced during reading [35].

The relationship between blink rate and cognitive load is often found to be inverse. The fundamental hypothesis from earlier studies is that when cognitive load is at its lowest, we blink more frequently because we believe we can blink without missing anything. Moreover, blinking inhibition may be an adaptive strategy that shields delicate cognitive processes from disruption when a mental load is raised [66].

The number of fixations in eye-tracking data can provide insights into several aspects of visual processing, attention, and cognitive engagement. The number of fixations might indicate which parts of a visual environment appeal to the user. A scene with a higher fixation number may show that the user finds that area more visually attractive or interesting. The number of fixations may also be a good indicator of the difficulty of a task or stimuli. As we expect that a user moves his eyes to absorb information and make sense of the visual input. Scene 2 had the highest number of fixations which suggests the high level of users' interest in this scene. Increasing the number of fixations in scene 3 may suggest that the user spent more time processing and integrating information from various scene areas. We assumed that participants would look more at the solar energy power, the output, of the system they already built simultaneously with trying a new design. This process attracted users' attention and motivated them to try different design scenarios.

A high number of fixations, which occur when a user revisits the same place or object repeatedly, may indicate a high level of interest. That might, however, also be a sign of understanding issues [67]. It's crucial to know that fixations number may not always give a full understanding of visual processing. Other eye-tracking elements, such as fixation duration, saccades or sensory data, should be considered to interpret the data precisely. It is important to note that eye-tracking research is a complicated field, and analysing data should be done in conjunction with other relevant measures.

Our findings indicated the importance of capturing several physiological data for monitoring the user experience. Data from eye tracking can be highly helpful in testing the usability and user experience of any VR game. The capacity of eye tracking to detect variations in involvement during particular tasks enables the researcher to link particular contexts to particular outcomes and demonstrate that engagement was the mediating factor [59]. Researchers can also learn more about the motivations behind users' responses and behaviours as they engage with photorealistic items, environments, and pretty much any stimuli by submerging research participants in a virtual reality world.

VII. Summary

We summarise our findings and illustrate how our results are aligned with our original research hypotheses (H).

H1: We hypothesized that diverse emotional responses within the three scenes would produce various attention patterns. Results from our study showed that the user experience and engagement level could be estimated by analyzing eye-tracking data, as the eyes can reveal much more about a person's emotions than most people realize and are a slightly more enigmatic indicator of their emotions. The number of fixations might indicate which parts of a visual environment appeal to the user. Scene 2 had the highest number of fixations, which suggests a high level of users' interest in this scene. Increasing the number of fixations in scene 3 may suggest that the user spent more time processing and integrating information from various scene areas.

H2: We predicted that pupil dilation would be affected by the users' engagement and performance in the VR application in different scenes. Our results showed increased pupil dilation in scene 2, which had a lower average brightness level than in scenes 1 and 3. This was aligned with the literature that the pupil size and brightness of the visual environment are found to be inversely proportional. This finding suggests the importance of considering the effect of visual brightness on pupil size while reliably measuring the user experience in virtual reality applications. Moreover, when comparing scenes 1 and 3, there is no significant difference in the average brightness level between them, but the pupil dilation in scene 3 is larger than in scene 1. This indicated the relationship between pupil dilation and task difficulty, increasing the level of interest and arousal and users' attention.

H3: It was hypothesized that utilizing an approach that increased cognitive load when teaching a topic to students would have an adverse effect on their performance. Our results showed that cognitive load in scene 1 is higher than in scenes 2 and 3. This was to be expected because participants needed to read and understand the role of the solar energy system components, as there is a lot of text in this scene. Our findings indicated the relation between the blinking rate and task difficulty. The blinking rate in scene 1 was lower than in scenes 2 and 3, as the task in scene 1 was very easy to perform. This aligned with the finding from the study by Tanaka and Yamaoka, which shows that the blinking rate with the difficult task was higher than for the easy task.

VIII. Conclusions

This paper highlights how combining multimodal data channels, which include a variety of objective and subjective metrics, can offer insights into a more comprehensive understanding of learner engagement and evaluate user experience. We compared the captured data in each scene of a VR solar energy systems design task to investigate learner engagement levels. We found that heart rate data do not significantly represent users' engagement. Our findings also showed that analysing reliable eye-tracking and vital signs data allows designers and developers to understand users better and design intuitive applications that meet their expectations. The impact of these findings is multifaceted, as they contribute to understanding user engagement and experience in immersive virtual environments. By highlighting the importance of multimodal data channels and revealing the limitations of heart rate data in representing user engagement, our paper offers valuable insights for developers, designers and educators.

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