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Effects of social interaction on virtual reality cybersickness☆

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ABSTRACT

Cybersickness is a well-known issue that creates barriers to the broad usage of virtual reality (VR) in real-life scenarios. It is essential to explore the factors influencing cybersickness and intervention strategies to alleviate cybersickness. In this study, social interaction is considered a potentially promising approach to addressing cybersickness. A total of 30 participants were recruited to join both social and solitary experimental tasks in VR experiments. The subjective and objective experiences in relation to cybersickness in VR were collected. The results indicated that social interaction could mitigate the sense of cybersickness. Significant differences were observed in verbally rated cybersickness, physiological measurements, and machine learning classifications. Random forest models were constructed to classify the severity of VR cybersickness and identify the feature importance in detecting cybersickness. This study is the first to explore the role of social interaction in VR cybersickness and raises new possibilities for researchers and designers to address this issue.

1. Introduction

Virtual reality (VR) is an increasingly prevalent technology that enables users to interact in a shared virtual environment. It has been utilized in various fields such as education, entertainment, and work. However, a common side effect associated with VR usage is cybersickness, also known as simulator sickness or motion sickness [1,2]. Cybersickness manifests as discomfort and malaise feelings brought on by exposure to VR [3]. Users may feel nausea, fatigue, headache, etc. in the use of VR [2]. These side effects have been recognized as a barrier to the widespread adoption of VR in real-world applications [4].

Researchers have investigated the causes and factors related to cybersickness, with sensory mismatch being a common reason for its occurrence [5,6]. It is characterized by a mismatch between the expectations based on past experiences and the inputs from the vestibular system, proprioceptors, and vision [6]. The factors that impact cybersickness include prior experience [7], individual differences [4], virtual environments [8,9], and interaction modes [10].

To alleviate cybersickness, interventions, and strategies such as drugs and adaptation techniques have been proposed. Drugs can be categorized into antimuscarinics, H1 and anti-histamines, and sympathomimetics, but they have crucial side effects such as fatigue, drowsiness, and dry mouth [11]. Adaptation or habituation is an effective non-pharmacological countermeasure, which can be achieved through exposure to virtual environments [11,12]. Recent research has shown that repeated exposure to VR can help reduce cybersickness, even after just one repetition [13]. However, this process may be time-consuming, as the adaptation period might last for several days and require two or more exposures [14]. Furthermore, the benefits of repeated exposure seem to be specific to a similar VR experience [13]. In other words, practicing with one VR scenario may not necessarily translate to improved tolerance in a different one.

Multisensory stimulation, such as olfactory, tactile, and auditory cues, has also been used to mitigate cybersickness [15–17]. For instance, pleasant odors and relaxing music have shown promise as countermeasures [16,18]. Additionally, combining galvanic cutaneous and auditory stimulation significantly reduced cybersickness [15]. Other potential countermeasures include controlled breathing [19], control central field-of-view [20], and acupressure [21]. However, The effectiveness of these interventions is questionable, as many of them remain

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controversial and require further investigation [11].

The advancement of technology has led to the emergence of VR as a social place where people can communicate and work together remotely [22]. Similarly, social interaction has become more common in autonomous vehicles, with working and communication being the primary activities for passengers [23,24]. However, the relationship between social interaction and cybersickness remains unclear.

This research paper aims to investigate the effects of social interaction on cybersickness in VR. To achieve this, an experiment was conducted in VR scenarios where participants performed comparable tasks in both solitary and social settings. Subjective methods, supported by physiological measurements, were collected and analyzed. Our findings suggest that social interaction could be a potential approach to mitigating cybersickness. Our study also demonstrates the potential and advantages of using multi-sensory physiological data to investigate the effects of social interaction on cybersickness.

2. Background and related work

There are many theories proposed to explain the symptoms of cybersickness. Some of the most prominent theories include the sensory conflict theory [25], the sensory rearrangement theory [5], the multisensory reweighting theory [26], the evolutionary theory [26], and the ecological theory [27]. The sensory conflict theory suggests that cybersickness occurs when there is a mismatch between the sensory information received by the individual and their expectations based on prior experiences. This theory is widely accepted but is not easily testable or falsifiable [28]. The sensory rearrangement theory, building upon sensory conflict theories, posits that cybersickness is triggered by discrepancies between the expected sensory stimulation and the actual sensory stimulation received. It is sometimes referred to as neural mismatches [5]. The multisensory reweighting hypothesis extends the sensory conflict theory and suggests that an individual's susceptibility to cybersickness is linked to their ability to quickly reweight conflicting multisensory cues in virtual environments [26]. The evolutionary theory views cybersickness as an adaptive response that helps the body respond to perceived poisoning. It argues that the symptoms of cybersickness are a result of the body trying to protect itself from potential toxins [29]. The ecological theory, also known as the postural instability theory, proposes that cybersickness occurs when the body is unable to properly adjust its posture in response to external stimuli. This theory suggests that the destabilizing effect of virtual environments can lead to feelings of discomfort and sickness [28].

These theories provide different perspectives on the causes and mechanisms of cybersickness. Among the various theories proposed, the sensory conflict theory and the multisensory re-weighting hypothesis appear to be the most suitable for understanding the impact of social interaction on cybersickness. In addition to these cybersickness theories, theories related to user experience and presence may also help explain the relationship between social interaction and cybersickness.

2.1. Sensory conflict theory and multisensory re-weighting theory

Sensory conflict theory proposes that the sensation of cybersickness emerges when there is a disparity between the sensory input we anticipate and the actual sensory stimuli we experience [30]. In other words, cybersickness occurs when the signals from our different senses contradict each other or fail to match our expectations based on previous experiences [30]. Visual stimuli are often the main source of conflicts in virtual environments [31].

The multisensory re-weighting hypothesis, grounded in sensory conflict theory, suggests that sensory cues that do not provide valuable information about the world or the body are given less importance. Meanwhile, cues that are reliable, like visual cues, are prioritized over other cues [26]. As a result, user factors become crucial in determining the likelihood and intensity of cybersickness experienced during extended reality exposure [26].

According to these theories, the severity of the neural mismatch could potentially vary depending on the level of attention given to each sensory input, which in turn affects behavior control. Research has shown that engaging in tasks or distractions can significantly reduce the occurrence of cybersickness [32]. One possible approach to alleviate cybersickness is by implementing pleasant smells and enjoyable music, as they have the potential to impact attentional resources and modify the processing of multiple stimuli [26]. Social interaction can also serve as a form of mental distraction that helps alleviate cybersickness among VR users or vehicle passengers. When individuals are engaged in social interaction and communication, their attention may shift towards the presence of others, diverting it from the uncomfortable sensations associated with cybersickness.

2.2. Presence and cybersickness

Presence, in this context, refers to the subjective feeling of being immersed in a virtual environment, even though physically located elsewhere [33,34]. It is the perception of "being there" within the virtual space [35]. Different types of presence have been studied, including spatial presence, which is the illusion of being physically present in a mediated room, social presence, which is the illusion of being present with other mediated individuals, and co-presence, which combines both these illusions [36]. Research has shown that individuals who experience a stronger sense of presence in virtual environments are less likely to experience less cybersickness [3].

Social interactions play a vital role in enhancing presence in a virtual environment. Engaging in social interactions can increase the sense of engagement and connection with others, thereby enhancing the feeling of being present in the virtual space. Moreover, the presence of more social cues can further increase the sense of presence and closeness [37]. Therefore, when individuals engage in social interactions within a virtual environment, it can enhance their sense of presence, potentially reducing the likelihood and severity of cybersickness.

2.3. Experience and cybersickness

In addition to the traditional theories explaining cybersickness, recent research suggests that psychological factors and placebo responses also play a role in cybersickness symptoms [38]. This means cybersickness could be intervened through psychological methods. When individuals have positive expectations and beliefs about a particular treatment or measure, they may perceive a reduction or alleviation of cybersickness symptoms, even if the treatment does not directly address sensory conflicts or postural adjustments.

Meanwhile, previous research suggested that social interaction has positive psychological effects and that collaborative activities are more enjoyable and engaging than solitary ones [39,40]. Engaging in social interaction with another person can improve user experiences, including the sense of social presence and immersion [41]. The presence of another person can also enhance engagement and add new value to the experience [42]. These positive effects of social interaction may contribute to a reduction in the sense of cybersickness.

3. Methods

3.1. Virtual environment and apparatus

Two virtual environments were created using Unity to represent the conditions of social experience and solitary experience. The two scenarios had different maps but shared similar styles, luminance, and contrast. Fences were utilized to establish a border to limit the movement area, with the playable areas being of the same size. Fig. 1 shows a screenshot of the environment.

In the virtual environment, participants could move through

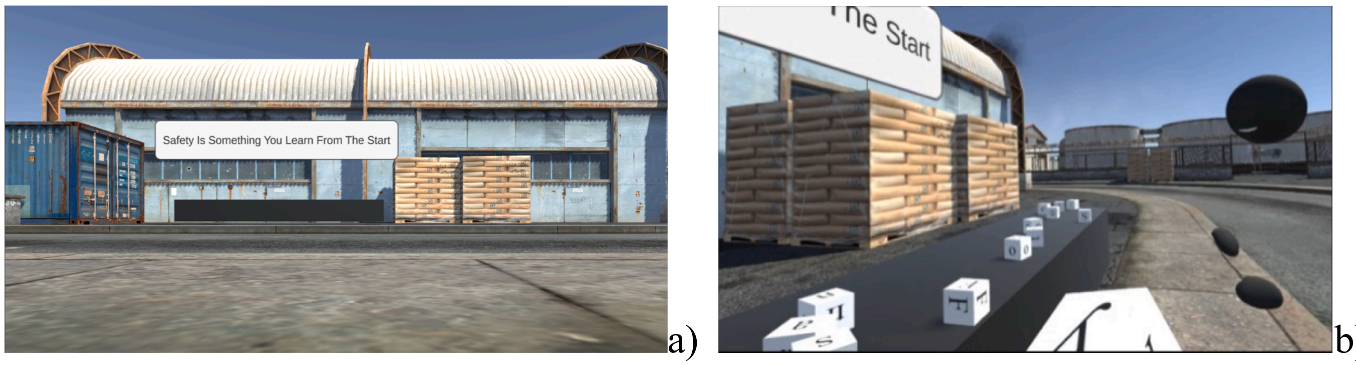

Fig. 1. A) screenshot of the virtual environment used in the experiment; b)A first-person perspective from the participants.

teleportation using the right controller. Participants moved forward according to their face direction, with the longest teleportation distance being six meters. They could interact with and grab gaming props using the left controller. Networking between VR users was facilitated using the Normcore toolkit.

For the experiment, commercially available Oculus Quest 2 HMDs were used, with each having a resolution of 1832x1920 pixels per eye. The HMDs were connected to a computer equipped with Windows 10, an Intel Core i5-8400 CPU, a 6 GB NVIDIA GeForce GTX 1060 GPU, and 16 GB RAM. The experiment was carried out in a laboratory with an office desk.

3.2. Task and experiment design

Participants were recruited to engage in a spelling game inspired by prior research on social collaboration using a word puzzle game [43]. Participants carried the alphabet cubes to spell out a sentence on the banner. The game involved carrying alphabet cubes to spell out a 37-character sentence on a banner. The alphabet cubes were scattered throughout the virtual environment, and participants were instructed to collect as many correct cubes as possible within 21 min, as previous research has suggested that using VR for more than 20 min can induce cybersickness [44]. To increase the complexity and diversity of the task, some "wrong" or "repeated" alphabet cubes were also included in the scene.

The within-subjects experiment consisted of two phases: solitary and social conditions (Table 1). In the solitary condition, participants completed the task alone, searching for alphabet cubes and assembling the sentence on their own. In the social condition, a same actor –an assistant - was presented as a collaborative partner for all participants, with the goal of maintaining consistency in presentation and collaboration mode across all participants [45]. Participants and the assistant could communicate and collaborate to assemble the sentence, sharing information about their location, the location of targeted alphabet cubes, and the alphabet they were seeking. They had a shared goal which was the "sentence" on the banner. Furthermore, the task was designed to simulate symmetric collaboration, with both users performing equal collaborative roles rather than one person leading the other. The order of the two conditions, solitary and social, was counterbalanced.

Table 1
Comparison between solitary and social tasks.

Terms	Solitary condition	Social condition
Map size	Same	Same
Max moving distance per step	Same	Same
Number and location of cubes in the map	Same	Same
Sharing information about the task through the headphone	No	Yes
Communication through the gesture and movement of avatars	No	Yes
Passing the cubes	No	Yes
Message irrelevant to carrying out the task	Not allowed	Not allowed

3.3. Participants

A total of 37 individuals participated in the study. Four participants were excluded from all analyses due to the absence of experiment phase two. One participant was excluded due to missing psychological data, while two participants were excluded for not actively participating in the experiment. The remaining 30 participants who completed both phases of the experiment were included in the analysis. Among them, there were 12 females and 18 males, with an average age of 26.23 ± 4.80. It was found that 33.3% of participants had no previous experience playing 3D games, with a low level of familiarity ($M = 2.23$, $SD = 1.16$, measured on a 5-point Likert scale from 1 (never) to 5 (every day)). Similarly, 12 participants had never used VR, 13 participants had only used VR on a few occasions, while only 5 participants had used VR frequently. Their familiarity with VR was also low ($M = 1.93$, $SD = 1.11$). Additionally, 22 out of the 30 participants reported prior experience with cybersickness in vehicles. The present study was ethically approved by the university ethics committee.

3.4. Data collection

Surveys are widely employed as a means of evaluating the subjective experience of cybersickness. A particular survey, known as the Fast Cybersickness Scale (FMS), has been specifically developed for measuring temporal changes during the use of VR. The FMS consists of a 20-point scale, where participants verbally rate their feelings of cybersickness per minute [46]. However, during the pilot study, we found that the original FMS per minute interrupted the participants' task completion, particularly in the social task, which required communication and collaboration. Therefore, in the formal experiment, participants were asked to verbally rate their cybersickness every three minutes, with instructions to pay attention to nausea, general discomfort, and stomach issues, and rate their feelings on a scale from 0 (no sickness at all) to 20 (frank sickness).

To consolidate our findings, we also collected additional data on user mental workload using the Subjective Mental Effort Questionnaire (SMEQ) [47] and user presence using the iGroup presence questionnaire (IPQ) [48]. The SMEQ proved to be highly effective in assessing mental effort, with respondents rating their perceived difficulty on a continuous scale ranging from 0 ("not at all hard to do") to 150 ("extremely hard to do"). IPQ, on the other hand, consisted of 14 items rated on a 7-point Likert scale, which were divided into three subscales: spatial presence, involvement, and experienced realism. Additionally, one item measured the participants' general sense of presence. As for objective task performance, we calculated the number of cubes carried by each participant.

In addition to surveys, physiological methods such as photoplethysmography (PPG), electrodermal activity (EDA), and skin temperature (SKT) can be used independently or as a complementary technique to assess cybersickness [49]. Therefore, we recorded physiological data using the wearable physiological recording system ErgoLAB V3.0 (Kingfar International Inc.). EDA, PPG, and SKT sensors were used to record signals, with EDA recorded using two electrodes placed on the left wrist to minimize the influence of clicking the VR button [50]. The SKT sensor was placed on the fourth finger of the right hand, and PPG recorded each subject's pulse at the left earlobe. Physiological data were recorded at a rate of 64 samples per second.

3.5. Procedure

Fig. 2 illustrates the experimental process. Upon arriving at the laboratory, participants were provided with an information sheet about the study and asked to complete an ethics consent form. Participants were instructed to abstain from consuming caffeine-containing beverages and smoking for two hours and to avoid consuming alcohol or medication for 24 h prior to each experimental phase.

Then participants joined a training session to familiarize themselves with VR technology and interact with virtual environments. The experimenter explained the task, and participants practiced until they were comfortable operating the VR equipment. After the training session, participants were given a break and asked to provide demographic information. All 30 participants reported no feeling of cybersickness after completing the training session.

Before each experimental phase, participants completed a pre-experiment questionnaire. Baseline data for physiological measures, including PPG, EDA, and SKT, were recorded for 2 min while participants remained seated in the laboratory. Participants were then randomly assigned to either the solitary or social condition and completed a 21-minute task while seated in a chair.

Throughout the experiment, participants were asked to verbally rate their feelings of cybersickness from 0 to 20 every three minutes. Physiological data were also recorded during the experiment. Participants were instructed to notify the experimenter if they felt too uncomfortable to continue and the experimenter would help them leave the virtual environment right away. Additionally, we would terminate the experiment if participants reported a cybersickness rating exceeding 15 due to ethical considerations.

After completing the experiment, participants left the virtual environment, and physiological measurements were recorded again for 2 min. Finally, the participants were asked to complete a questionnaire that was based on the IPQ and SMEQ. Participants were instructed to take a break until they no longer experienced any symptoms of cybersickness before leaving the laboratory.

Participants were given one day to relax to diminish the influence of cybersickness in phase 1, as the impact of cybersickness can last from 30 min to several hours after exposure [51]. The procedure for phase 2 was identical to that of phase 1.

3.6. Data analysis

The collected data were pre-processed using the data analysis modules of the ErgoLAB V3.0 for heart rate (HR), heart rate variability (HRV), EDA, and SKT. Subsequently, statistical analysis was conducted using SPSS. To reduce noise, we applied a moving average filter with a window size of 5 samples to smooth out the SKT and EDA signals. The PPG pulse signal was detrended and wavelet denoised to eliminate any piecewise polynomial trend. The R peak was extracted with a maximum heart rate of 120 bpm and a 40% R-peak mark threshold. Ectopic was detected with a median sample point of 4 and replaced with a median method. Additionally, low frequency (LF), high frequency (HF), and LF/HF were calculated using the power spectral density (PSD) estimate technique. The frequency range of HF, which indicated sympathetic nervous system activity, was 0.15 to 0.4 Hz. LF ranged from 0.04 to 0.15 indicating the action of the sympathetic nervous system and parasympathetic nervous system [52].

The 21-minute experiment data were segmented into seven epochs, each containing 3 min. The mean and standard deviation of SKT, EDA, and HR scores for the pre-experiment, after-experiment, and each segment were calculated. To eliminate any individual homeostasis bias, the following formula was used to calculate delta (Δ) scores for each participant [53]. FMS $_{\text{baseline}}$ refers to the initial FMS score at the beginning of the experiment.

$$\Delta \text{FMS}_{\text{minute } x} = \text{FMS}_{\text{minute } x} - \text{FMS}_{\text{baseline}} \quad (1)$$

$$\Delta \text{ EDA}_{\text{minute } x} = \text{EDA}_{\text{minute } x} - \text{EDA}_{\text{baseline}} \quad (2)$$

$$\Delta \text{ SKT}_{\text{minute } x} = \text{SKT}_{\text{minute } x} - \text{SKT}_{\text{baseline}} \quad (3)$$

$$\Delta \text{ HR}_{\text{minute } x} = \text{HR}_{\text{minute } x} - \text{HR}_{\text{baseline}} \quad (4)$$

To analyze the data, we conducted a Shapiro-Wilk test to assess the normality of the distributions of both the subjective and physiological measures. The results indicated that the measures violated the normality assumption. Therefore, nonparametric Friedman and Wilcoxon signed-rank tests were performed using SPSS.

Machine learning models were employed to distinguish solitary and social conditions and estimate FMS scores based on physiological data. In our study, we chose to employ the Random Forest model, which is well-known for its effectiveness in classification tasks. This choice was suitable for our experimental setup, with a small number of data but a large number of features to consider. Additionally, the Random Forest model demonstrates robust performance against overfitting, alleviating

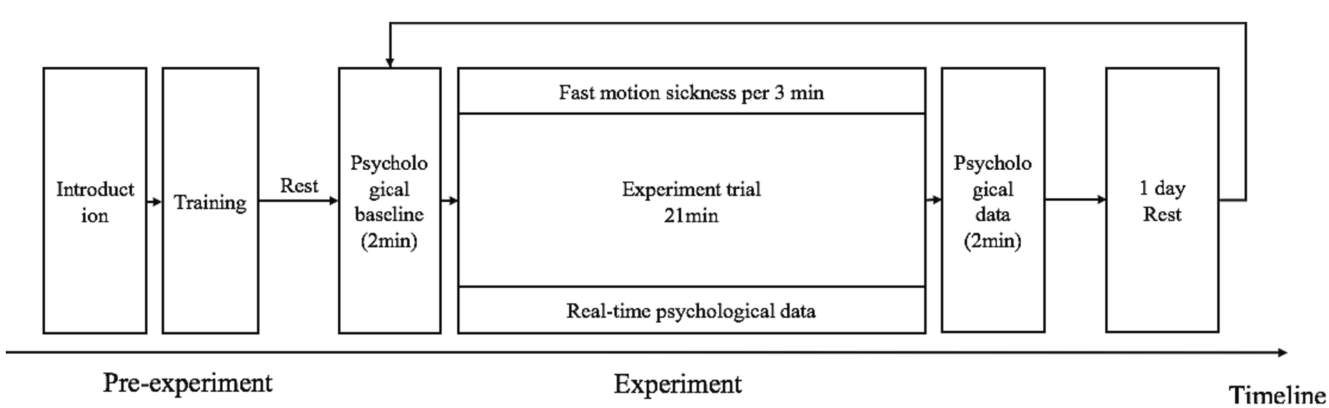

Fig. 2. Experiment process flow describing the two experiment phases and the gathering of data.

the need for feature normalization [54].

The main purposes of using machine learning methods are twofold. Firstly, we aim to differentiate between solitary and social conditions, and secondly, to predict the severity of cybersickness using the FMS score, classifying individuals as 'sick' or 'non-sick'. A total of 11 features were selected based on previous research on physiological data [54]. The data were divided into a training set (80%) and a test set (20%). Features of physiological data were calculated every three minutes to align with the subjective FMS scores. The feature vector included:

EDA: mean and standard deviation
PPG: mean HR, mean Inter-Beat Interval (IBI), HRV characteristics (i.e., RMSSD, pNN50%, LF/HF), and nonlinear characteristics (i.e., SD1, SD2).
SKT: mean and standard deviation

The machine learning results are evaluated based on precision, recall, and F1-score. The F1-score, which is calculated as the harmonic mean of precision and recall, is especially useful when dealing with imbalanced data distributions.

F1 = (2 * (precision * recall) / (precision + recall)) (5)

4. Results

4.1. Completion time and task performance

Among the 30 participants, six were too sick to finish the experiment in the solitary condition, while one didn't fully complete the social condition. Of these 7 participants, 3 aborted the experiment within 12 to 15 min, and 3 exited in the 15–18 min epoch. One participant in the social condition exited during the period of 18–21 min (Table 2). These participants reported a cybersickness score of 16 just before leaving the experiment since we explained in the instruction that the participants would stop the experiment if their fast cybersickness was greater than 15. 23 of the 30 participants wholly complete the tasks under two conditions.

We conducted calculations to determine the accurate number of cubes carried by participants during the experiment. After performing the Wilcoxon Signed Rank test, we found no significant difference between the two conditions (Z = -1.004, p = 0.316) (M = 20.20 ± 7.75 for solitary condition, M = 18.30 ± 4.64 for social condition).

4.2. Verbal cybersickness rating

A non-parametric related-samples Wilcoxon signed-rank test was conducted to examine the Δ FMS scores, with social interaction (solitary and social conditions) and time (seven time epochs) as within-subjects factors. Results from the Wilcoxon test indicated that cybersickness scores in solitary conditions from 0 to 12 min were significantly higher than those in social conditions (p = 0.005, p = 0.005, p = 0.020, p = 0.045, respectively) (see Table 3). No significant differences were observed in the highest FMS scores, namely peak FMS (Z = -1.755, p = 0.079). Fig. 3 indicates the average FMS scores in solitary and social conditions respectively. The increase in FMS in the social condition was smaller than that in the solitary condition.

The Friedman's test revealed a significant effect of time ($\chi2(2)$ = 126.882, $p < 0.001$ for solitary condition, and $\chi2(2)$ = 121.496, $p < 0.001$ for social condition respectively), indicating that cybersickness scores increased with longer durations of VR use. Moreover, a significant difference was observed between phase 1 and phase 2 for the highest FMS (Z = -3.479, p = 0.001), suggesting that participants experienced less cybersickness during their second attempt at the task (M = 8.57 ± 5.94 for phase 1 & M = 6.23 ± 4.01 for phase 2).

Table 2
Number of participants who completed or aborted the experiment.

Duration	Solitary condition	Social condition
Within 12–15 min	3	0
Within 15–18 min	3	0
Within 18–21 min	0	1
Over 21 min	24	29

Table 3
FMS score comparison of solitary and social condition (Wilcoxon test).

Δ FMS	$M_{Solitary}$-M_{Social}	Z	p
0–3 min	1.2	−2.828	0.005*
3–6 min	1.1666	−2.801	0.005*
6–9 min	1.5333	−2.329	0.02*
9–12 min	1.8333	−2.004	0.045*
12–15 min	1.8333	−1.949	0.051
15–18 min	1.8333	−1.806	0.071
18–21 min	1.6334	−1.647	0.1

* $p < 0.05$.

4.3. Mental effort and sense of presence

Wilcoxon Signed Rank test did not find any significant differences for SMEQ between the two conditions (Z = -1.402, p = 0.161). However, it is worth noting that the mental effort required for the solitary condition was rated as "Fairly hard to do" (M = 39.38), while the social condition required less mental effort and was rated as "A bit hard to do" (M = 31.79).

Similarly, the Wilcoxon Signed Rank test did not find any significant differences for all IPQ subscales. Participants in the social condition had a slightly higher presence in terms of general presence, involvement, spatial presence, and experienced realism, however, the differences were not significant (Table 4).

4.4. Physiological measurement

A non-parametric related-samples Wilcoxon signed rank test of Δ EDA indicated a significant difference in EDA between social and solitary conditions in the 12–15 min epoch (Z = -2.085, p = 0.037) and after the experiment (Z = -2.612, p = 0.009). The changes in EDA in the social condition were significantly lower than those in the solitary condition.

Furthermore, a related-sample Friedman's two-way ANOVA indicated that there was a significant effect of time epoch on EDA ($\chi2(2)$ = 61.77, $p < 0.001$ for solitary condition, and $\chi2(2)$ = 55.88, $p < 0.001$ for social condition). As shown in Fig. 4, EDA increased across the experiment epochs compared to the baseline period. Δ EDA demonstrated an increasing linear trend during the experimental period, with the increase in EDA in the social condition being smaller than that in the solitary condition.

The results also showed a statistically significant difference in Δ SKT between the solitary and social conditions from 6 to 15 min (Z = -2.02, −2.22, −2.01, p = 0.044, 0.026, 0.045, respectively). The slope of SKT in the social condition was smaller than that in the solitary condition. During VR use, there was a significant increasing trend in SKT across time epochs ($\chi2(2)$ = 47.15, $p < 0.001$ for solitary condition, and $\chi2(2)$ = 23.49, p = 0.001 for social condition), which decreased during the rest period. Fig. 5 illustrates the Δ SKT in both conditions.

In addition, the HR in the time period of 12–15 min was significantly higher in the solitary condition than in the social condition (Z = -2.00, p = 0.046). A significant difference across the time epochs was also found ($p < 0.001$). However, the trends in HR between solitary and social conditions differed. Participants' HR increased in the solitary condition, whereas in the social condition, the initial increase in HR from 0 to 6 min turned into a decreasing trend from 9 to 21 min. Moreover, the time influence on HR was not significant. Fig. 6 shows the different trends in HR.

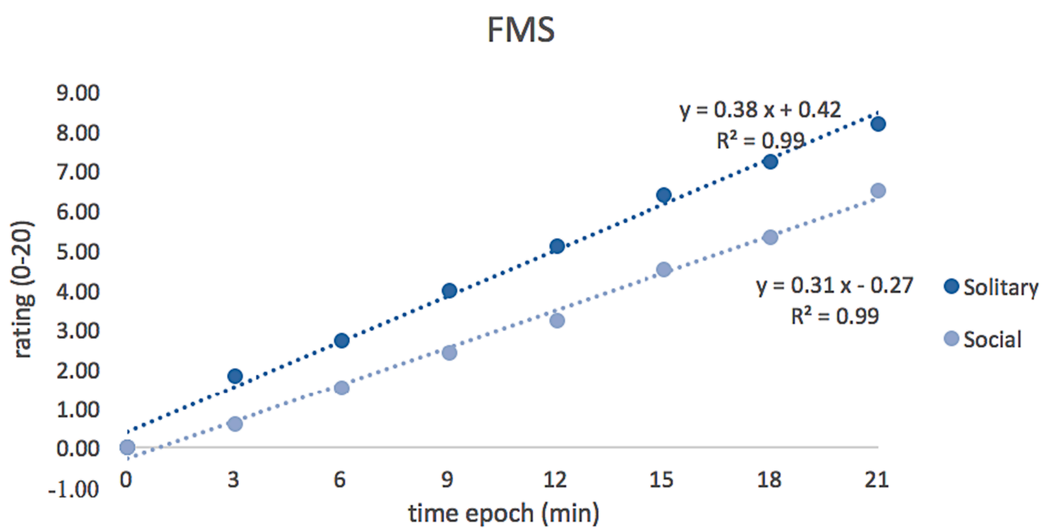

Fig. 3. Plot of Δ FMS scores per epoch in solitary and social conditions.

Table 4
Means, standard deviations, and p-value of the measured variables.

Duration	Solitary condition	Social condition	Z	P-value
General presence	5.03	5.14	−1.004	0.315
Involvement	4.19	4.35	−0.63	0.529
Spatial presence	4.77	4.94	−1.07	0.285
Experienced realism	3.65	3.85	−1.08	0.278
Total IPQ	3.94	4.11	−1.30	0.194

4.5. Machine learning classification results

This section presents the results of two classification tasks using the Random Forest Classifier. These tasks aimed to distinguish solitary and social tasks and explore the relationship between verbally assessed cybersickness and psychological measurements.

4.5.1. 'solitary' and 'social' tasks classification results

The accuracy of the solitary and social task predictions was evaluated using precision, recall, and F1-score metrics. The result is reported in Table 5.

The Random Forest model demonstrated a balanced performance in distinguishing between solitary and social tasks, with precision, recall, and F1-score metrics all around 0.75. This indicates that the model has the capability to accurately identify approximately 75% of the instances within the test set, highlighting the efficacy of the Random Forest model in differentiating between solitary and social tasks. Moreover, the model's high accuracy in classification suggests that there is a significant distinction in the physiological data observed between the social and solitary conditions. This further strengthens the findings from our previous statistical analysis.

4.5.2. 'sick' and 'non-sick' classification results

To better distinguish between participants who were considered 'sick' and 'non-sick', we established a designated threshold score of 3 on the FMS scale. Those individuals who obtained a score of 4 or above were labeled as 'sick', while those with a score of 3 or below were classified as 'non-sick' [54]. Using this categorization, we proceeded to train the Random Forest model on both the solitary and social datasets separately (Tables 6 and 7).

An accuracy of 0.83 and 0.86 indicates that the Random Forest Classifier demonstrates strong performance in accurately classifying participants as either 'sick' or 'non-sick' based on their FMS scores. Our model effectively leverages physiological data to distinguish the severity of cybersickness in both solitary and social tasks. Additionally, the

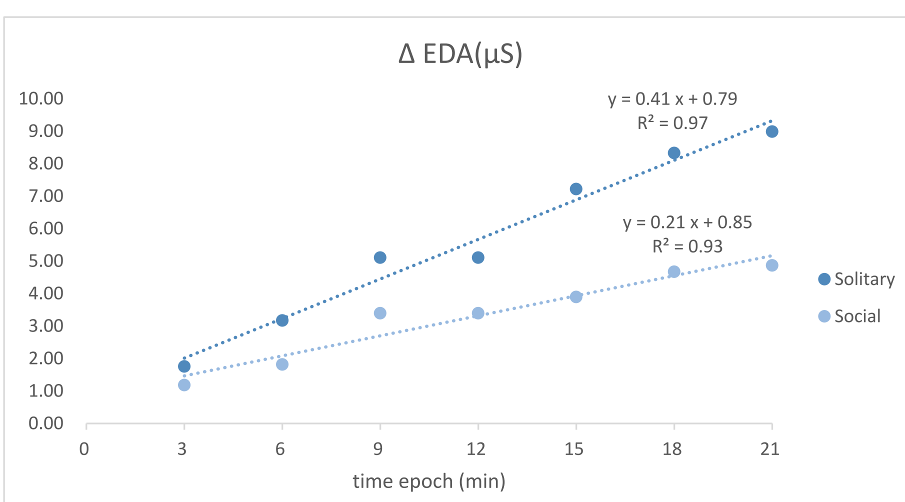

Fig. 4. Plot of Δ EDA per epoch in solitary and social conditions.

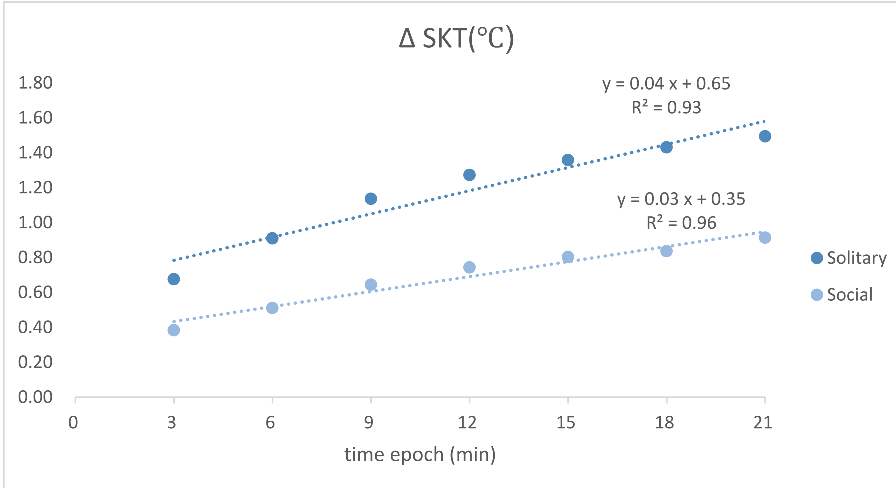

Fig. 5. Plot of Δ SKT per epoch in solitary and social conditions.

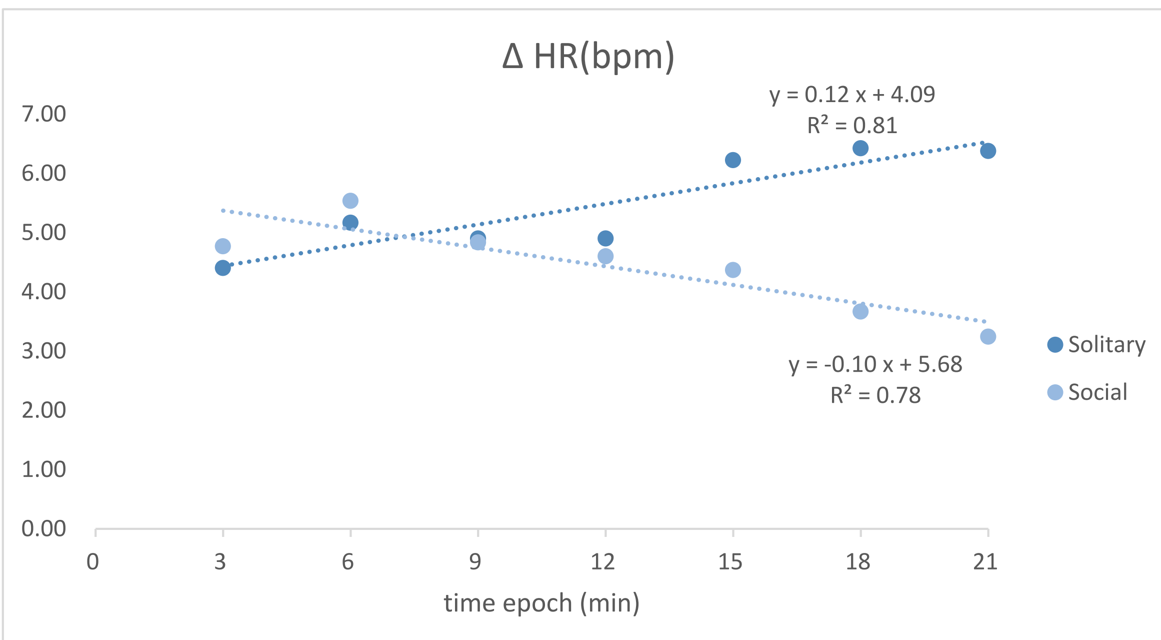

Fig. 6. Plot of Δ HR per epoch in solitary and social conditions.

Table 5
Precision, recall, F1-score of solitary and social tasks classification.

	precision	recall	F1-score
Solitary	0.77	0.76	0.76
Social	0.72	0.74	0.73
Accuracy	0.75	0.75	0.75
Macro avg			0.75

Table 6
Precision, recall, and F1-score of 'sick' and 'non-sick' participants in the solitary condition.

	precision	recall	F1-score
Non-sick	0.83	0.79	0.81
Sick	0.83	0.87	0.85
Accuracy	0.83	0.83	0.83
Macro avg			0.83

Table 7
Precision, recall, and F1-score of 'sick' and 'non-sick' participants in the social condition.

	precision	recall	F1-score
Non-sick	0.86	0.75	0.80
Sick	0.86	0.92	0.89
Accuracy	0.86	0.84	0.86
Macro avg			0.84

results from the two tables suggest that the model achieves slightly higher accuracy in social conditions.

Fig. 7 illustrates the average importance ranking of features for the Random Forest Classifier in both conditions. The length of the bars represents the level of importance, with longer bars indicating greater significance. A longer bar denotes a more critical value. In both the solitary and social tasks, the mean EDA (μS) and mean SKT (°C) were among the top important features. This result implies that these features

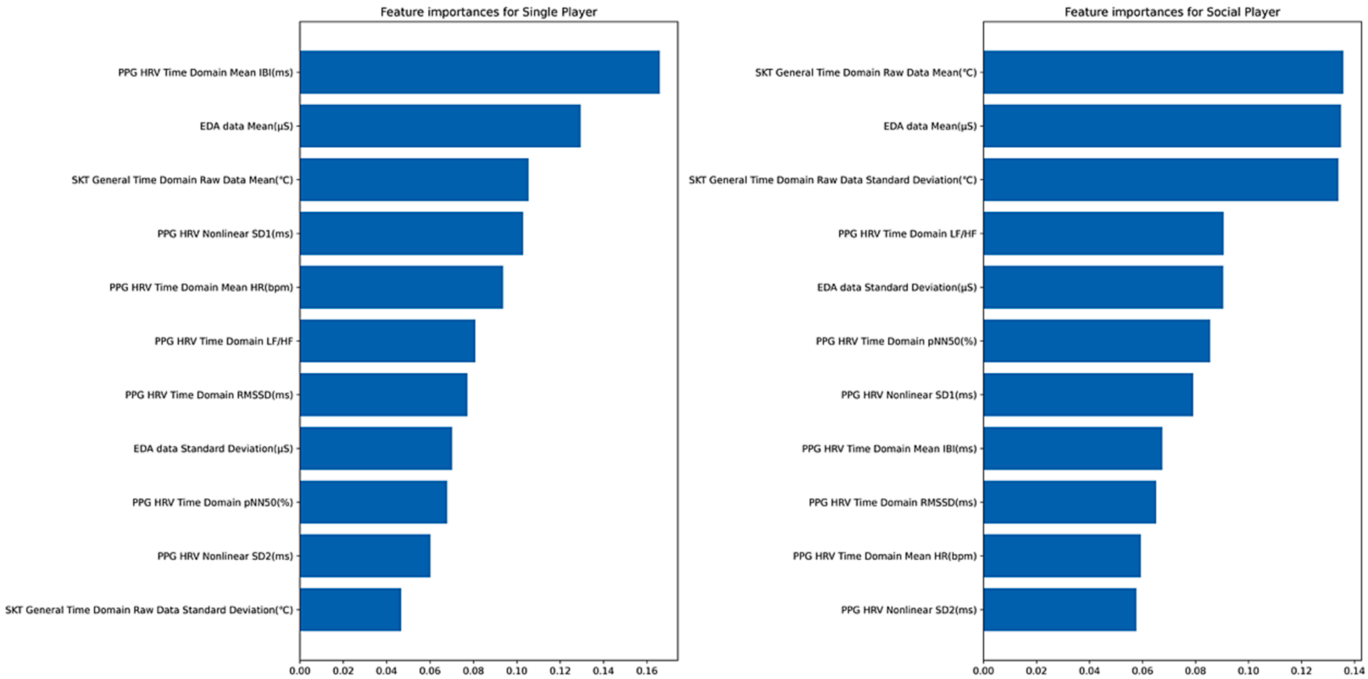

Fig. 7. Feature importance rank of Random Forest. a) Solitary task; b) Social task.

play a crucial role in predicting cybersickness in both types of tasks. The mean IBI (ms) is an important feature in solitary task. However, the importance of the Standard Deviation of SKT (°C), which represents the variability in skin temperature, varied between the two tasks. It was the least important feature for the solitary task, but the third most important feature for the social task. This suggests that the variability in skin temperature data may have a different impact on the prediction of cybersickness depending on the social context of the VR experience.

5. Discussion

5.1. Social interaction and cybersickness

This study proposes a new potential strategy for alleviating cybersickness through social interaction. The FMS scores indicated a significant effect of social interaction in the epoch of 0–12 min. In this period participants reported lower cybersickness during social collaboration tasks. Previous studies have suggested that cybersickness tolerance is influenced by technological and content factors [55] However, social factors, such as collaboration and competition, may also contribute to the heterogeneity of cybersickness. The positive effects of social interactions have been widely reported, with studies showing that working together can lead to a more enjoyable experience [40] and positive psychological effects [39]. It is suggested that collaboration provides a pleasant environment, which can reduce the sense of cybersickness. This is consistent with previous research indicating that a pleasant environment and sound can alleviate cybersickness [17,56]. It is assumed that individuals may experience more enjoyment and heightened arousal while in social settings, potentially providing a natural remedy for the negative effects of cybersickness [57].

Moreover, engaging in social interaction while using VR can help alleviate cybersickness. Social interaction enhances the feeling of being present in the virtual environment and acts as a mental diversion [58,59]. Participants in this study reported a stronger sense of presence, including spatial interactivity, navigation, and realism when engaging in social interaction compared to being alone. Previous research has also shown that there is a negative relationship between the presence and cybersickness [3,60]. A higher sense of presence can reduce cybersickness symptoms as it diverts individuals' attention away from the conflicting sensory signals contributing to the discomfort. Studies also showed that distraction, such as that provided by social interaction, can significantly decrease the severity of cybersickness [32]. Therefore, the distraction provided by social interaction may divert participants' attention from their physiological symptoms, contributing to a more immersive and less discomforting VR experience.

Lower workload may also contribute to the lower cybersickness experienced in social conditions. In our study, participants in the social group reported lower mental effort when completing the task compared to those in the solitary group. This finding aligns with previous research suggesting that task characteristics, particularly workload, have a significant impact on predicting cybersickness [61]. Therefore, the presence of others and collaboration in completing the task may reduce mental workload and divert cognitive resources away from potentially sickness-inducing visual-vestibular input, resulting in fewer cybersickness symptoms.

Differences were also observed in the psychological signals between solitary and social conditions. In particular, social interaction led to lower changes in EDA and SKT. EDA is a measure of autonomic nervous system activity, which is often linked to increased sweating and arousal [62]. It is also known to be associated with cybersickness and nausea. A number of studies have reported significant increases in EDA during cybersickness experiences [1,14,63]. Our study found that EDA increased during the experiment and that in some cases, excessive sweating caused the sensors to drop, which is consistent with previous research [64]. Furthermore, the changes in EDA were greater and increased more rapidly in the solitary condition than in the social condition. This suggests that working alone led to a higher degree of cybersickness experienced by participants.

The study found that there was an increase in the participants' sensitivity to touch (measured through their SKT on fingertips) in both the social and alone conditions. However, the increase was less pronounced when using an HMD in a social setting compared to when using it alone. This is consistent with previous research that found an increase in body temperature when watching visually induced cybersickness videos. [54]. Participants who experienced cybersickness symptoms had higher body temperature changes than those who did not [1]. Overall, these findings suggest that participants in the solitary condition experienced more cybersickness than those in the social condition.

However, It is important to note that the observed SKT changes in this study should be interpreted with caution. Some studies have found that SKT can remain lower than the baseline level even after exiting the VR environment [65]. This may be influenced by the type of task that participants engage in. Most previous studies on cybersickness have primarily relied on passive intervention methods, such as the implementation of pseudo-Coriolis intervention, the observation of videos, or the passive navigation of virtual environments [1,66]. This study employed active interaction tasks that required participants to achieve a specific goal. This may have resulted in higher engagement levels and a subsequent increase in SKT during the experiment.

Studies have shown that an increased heart rate is related to the autonomic nervous system's response to uncomfortable environments or psychological stress during VR usage [56,67]. Many studies suggested a relationship between increased heart rate and cybersickness [68–71]. In this study, the HR of participants in solitary tasks increased, potentially reflecting the experience of cybersickness [1,54]. Meanwhile, the HR of non-sick participants in social tasks remained stable.

In conclusion, the findings of this study, along with previous research, suggest that social interaction can affect the severity of cybersickness and may serve as a strategy to alleviate it. Nevertheless, the underlying mechanisms and neural pathways linking social interaction and nausea are still not fully understood. Consequently, further research is needed to validate our findings.

5.2. Implication for design and practice

This study has made significant contributions to our knowledge of cybersickness and provided both theoretical and practical contributions. The research findings have enabled us to understand the effectiveness of social interaction as a potential countermeasure against cybersickness. Additionally, the use of machine learning has allowed for the prediction of cybersickness levels based on multisensory physiological data. This knowledge can be valuable for future VR design and development.

The study's practical implications include the development of new intervention strategies that could be implemented to mitigate cybersickness in VR scenarios. Although the general experiment results suggested that social interaction leads to less cybersickness compared to solitary tasks, it is essential to note that the significant differences in psychological data (i.e., EDA, SKT, and HR) mainly appeared in the time epoch of 12–15 min, during which solitary participants began to exit the experiment. This may indicate that the influence of social interaction on cybersickness mainly appears after a certain time of VR use. As studies indicated that 80% of participants showed symptoms of cybersickness after 10 min of VR use [72]. Moreover, this effect of social interaction may vary in different task contexts and virtual environments, which remained further empirical evidence.

This study also highlights the importance of proper training before using VR in collaborative work. Previous findings validated the theory of adaptation to VR cybersickness [13,73]. As a result, a suitable training and adaptation process could assist users in becoming familiar with the environment and decreasing their experiences of cybersickness. All seven participants who exited the first phase of the experiment completed the 21-minute task in the second phase of the experiment. Moreover, the verbally rated cybersickness scores also significantly decreased in the second phase compared to the first phase. This finding suggests that participants became increasingly comfortable with the virtual environment as they spent more time in it, a result that is consistent with previous research indicating that users can adapt to and learn from VR experiences [11,13]. As a result, it is important to design training programs that not only provide operational guidance but also give users enough time to acclimate to their new digital surroundings.

Additionally, this study has practical implications for the detection of cybersickness in VR using machine learning models. The feasibility of predicting cybersickness levels based on multi-sensory physiological data was demonstrated. The findings also confirmed that psychological reactions to solitary and social tasks may vary, highlighting the possibility of different experiences of cybersickness based on these conditions. This discovery supports the need to separately examine the experiences of users in solitary and social settings [74]. Furthermore, stable and important indicators, such as the mean EDA, and mean SKT were identified in both scenarios, aligning with previous research [54]. These results suggest that physiological sensors could potentially be valuable in the development of systems to detect and predict cybersickness. The experiment and machine learning approach proposed in this study could benefit the design and development of a prediction system, which predicts and alerts users before showing symptoms of cybersickness.

6. Conclusion, limitation, and future research

This study represents a novel exploration of the potential impact of social interaction on VR cybersickness. The findings demonstrate that social interaction may offer a promising approach for reducing the sensation of cybersickness. This was demonstrated through both verbally rated scores (FMS), physiological measures (PPG, EDA, and SKT), and machine learning classification.

The study has opened up new ideas for researchers and designers in exploring the role of social interaction in cybersickness and the potential of machine learning for predicting cybersickness. In the future, this study could be expanded to investigate various effects of social interaction on cybersickness and its underlying mechanisms at the hormonal and neural levels. Studies have shown that participants exhibit different behavior patterns and engagement levels in the competitive version and the collaborative version [57,75]. Therefore, it would be interesting to explore different social interaction methods (i.e., collaboration or competition, equal or unequal, pleasant or unpleasant collaboration), social tasks, and different partner pairings in future research. Additionally, since only one research assistant collaborated with all participants in this study, future research could consider involving different users in the experiment and explore the relationship between partners and their influence on cybersickness.

Another potential limitation of our study is the lack of direct measurement of participants' physical movement or virtual distance traveled during the tasks. This information could have offered valuable insights into the relationship between activity level and cybersickness symptoms. To better grasp the impact of the activity on cybersickness in both social and solitary conditions, future studies should consider including objective measures of physical movement and virtual distance.

Furthermore, we chose wrist-based EDA placement for practicality and participant comfort. The wrist is a convenient and easily accessible location that does not interfere with participants' task performance, allowing them to wear the sensors for long periods comfortably [50]. Nevertheless, we acknowledge that collecting EDA data from the fingers or feet could provide more accurate and robust measurements. Research has demonstrated that both finger and foot-based recordings tend to be more sensitive than those obtained from the wrist [76].

Conducting repeated measures for cybersickness is also challenging. To address this challenge, we took steps to minimize the influence of cybersickness by scheduling the two experimental phases on different days, as recommended by previous studies [53,56]. However, it is important to recognize that various external factors, such as sleep patterns, fatigue levels, emotional states, and mental stress, could also affect cybersickness in real-world situations and should be taken into account in future research.

Finally, it is important to acknowledge that our study was conducted as an exploratory investigation with a relatively small dataset. To provide more robust evidence and further validate our results, future studies should aim to collect larger datasets and employ advanced signal processing techniques.

Declaration of generative AI and AI-assisted technologies in the

writing process

During the preparation of this work the author(s) used chatGPT in order to improve language, make it readable. After using this tool/service, the author(s) reviewed and edited the content as needed and take (s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Yifan Yang: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Xu Sun:** Supervision, Conceptualization, Methodology, Writing – review & editing. **Yaorun Zhang:** . **Han Zhang:** Writing – review & editing. **Xiaotong Sun:** . **Canjun Yang:** Funding acquisition, Supervision. **Ying Jing:** Conceptualization, Methodology. **Sheng Zhang:** Supervision, Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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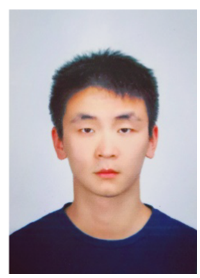

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