Towards physiological detection of a “just-right” challenge level for motor learning in immersive virtual reality: a pilot study protocol.

Samory Houzangbe, Martin Lemay, Danielle E. Levac

Submitted to: JMIR Research Protocols
on: December 21, 2023

Table of Contents

Towards physiological detection of a “just-right” challenge level for motor learning in immersive virtual reality: a pilot study protocol.

Samory Houzangbe[1]; Martin Lemay[2] PhD; Danielle E. Levac[1] PT, PhD

[1]School of Rehabilitation, Faculty of Medicine, University of Montreal CHU Sainte-Justine Research Center Montréal CA
[2]Department of Physical Activity Sciences Université du Québec à Montréal CHU Sainte-Justine Research Center Montréal CA

Corresponding Author:
Samory Houzangbe
School of Rehabilitation, Faculty of Medicine, University of Montreal
CHU Sainte-Justine Research Center
Centre de Réadaptation Marie Enfant, 5200 rue Bélanger
Montréal
CA

Abstract

Background: Motor learning, a primary goal of pediatric rehabilitation, is facilitated when tasks are presented at a ‘just-right’ challenge level: at the edge of the child’s current abilities, yet attainable enough to motivate the child in persistent efforts for success. Immersive virtual reality (VR) may be ideally suited for ‘just-right’ task challenge because it enables precise adjustments of task parameters in motivating environments. Rehabilitation-specific VR tasks often use dynamic difficulty algorithms based on task performance to personalize task difficulty. However, these approaches do not consider relevant cognitive processes that could also impact ‘just-right’ challenge, such as attention and engagement. Objective physiological measurement of these cognitive processes using wearable sensors could support their integration within ‘just-right’ challenge detection and prediction algorithms. As a first step towards this goal, it is important to explore relationships between objectively and subjectively measured psychophysiological state at progressively challenging task difficulty levels.

Objective: 1) Evaluate the performance of wearable sensors in a novel movement-based motor learning immersive VR task; 2) Evaluate changes in physiological data at three task difficulty levels; and 3) Explore the relationship between physiological data, task performance, and self-reported cognitive processes at each task difficulty level.

Methods: Within-participant experimental design. Twelve children and youth aged 8-16 years (six with cerebral palsy at Gross Motor Function Classification Levels I-II and six typically developing children) will be recruited to take part in a single 90-minute data collection session. Physiological sensors include electrodermal activity (EDA), heart rate, electroencephalography (EEG), and eye-tracking. After collecting physiological data at rest, participants will play a seated unimanual immersive VR task involving bouncing a virtual ball on a virtual racket. They will first play for three minutes at a pre-defined medium level of difficulty to determine their baseline ability level, and then at a personalized choice of three progressive difficulty levels for three minutes each level. Following each 3-minute session, participants will complete a short Likert-scale questionnaire evaluating engagement, attention, cognitive workload, physical effort, self-efficacy, and motivation. Data loss and data quality will be calculated for each sensor. Repeated-measures ANOVAs will evaluate changes in physiological response at each difficulty level. Correlation analyses will determine within individual relationships between task performance, physiological data, and self-reported data at each difficulty level.

Results: Research Ethics Board approval has been obtained and data collection is underway.

Conclusions: Wearable sensors may provide insights into physiological effects of immersive VR task interaction at progressive difficulty levels in children and youth with and without physical impairments. Understanding the relationship between physiological and self-reported cognitive processes is a first step in better identifying and predicting ‘just-right’ task challenge during immersive VR motor learning interventions.

(JMIR Preprints 21/12/2023:55730)
DOI: https://doi.org/10.2196/preprints.55730

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✓ **Please make my preprint PDF available to anyone at any time (recommended).**

Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.

Only make the preprint title and abstract visible.

No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✓ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v

Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Towards physiological detection of a “just-right” challenge level for motor learning in immersive virtual reality: a pilot study protocol.

Abstract

Background: Motor learning, a primary goal of pediatric rehabilitation, is facilitated when tasks are presented at a “just-right” challenge level: at the edge of the child’s current abilities, yet attainable enough to motivate the child in persistent efforts for success. Immersive virtual reality (VR) may be ideally suited for “just-right” task challenge because it enables precise adjustments of task parameters in motivating environments. Rehabilitation-specific VR tasks often use dynamic difficulty algorithms based on task performance to personalize task difficulty. However, these approaches do not consider relevant cognitive processes that could also impact “just-right” challenge, such as attention and engagement. Objective physiological measurement of these cognitive processes using wearable sensors could support their integration within “just-right” challenge detection and prediction algorithms. As a first step towards this goal, it is important to explore relationships between objectively and subjectively measured psychophysiological state at progressively challenging task difficulty levels.

Objectives: 1) Evaluate the performance of wearable sensors in a novel movement-based motor learning immersive VR task; 2) Evaluate changes in physiological data at three task difficulty levels; and 3) Explore the relationship between physiological data, task performance, and self-reported cognitive processes at each task difficulty level.

Methods: Within-participant experimental design. Typically developing children and youth aged 8-16 years will be recruited to take part in a single 90-minute data collection session. Physiological sensors include electrodermal activity (EDA), heart rate, electroencephalography (EEG), and eye-tracking. After collecting physiological data at rest, participants will play a seated unimanual immersive VR task involving bouncing a virtual ball on a virtual racket. They will first play for three minutes at a pre-defined medium level of difficulty to determine their baseline ability level, and then at a personalized choice of three progressive difficulty levels for three minutes each level. Following each 3-minute session, participants will complete a short Likert-scale questionnaire evaluating engagement, attention, cognitive workload, physical effort, self-efficacy, and motivation. Data loss and data quality will be calculated for each sensor. Repeated-measures ANOVAs will evaluate changes in physiological response at each difficulty level. Correlation analyses will determine within individual relationships between task performance, physiological data, and self-reported data at each difficulty level.

Results: Research Ethics Board approval has been obtained and data collection is underway.

Conclusions: Wearable sensors may provide insights into physiological effects of immersive VR task interaction at progressive difficulty levels in children and youth. Understanding the relationship between physiological and self-reported cognitive processes is a first step in better identifying and predicting “just-right” task challenge during immersive VR motor learning interventions.

Keywords: Virtual reality, pediatric rehabilitation, physiological data, engagement, just-right challenge.

Introduction

Virtual reality (VR) systems enable users to interact with virtual environments using body movements. Virtual environments can be categorized as immersive or non-immersive [1]. Immersive VR is viewed in a head-mounted display (HMD) that provides a stereoscopic 3D viewing medium in which visual display changes in a natural way with head movements [2]. User movements are tracked by hand-held or body-worn sensors to enable interaction with virtual objects. In contrast, non-immersive VR is viewed on a 2D flat-screen display. VR incorporates evidence-based motor learning principles (such as multisensory feedback and abundant repetitions) and engaging immersive environments that may motivate children to adhere to repeated practice [3–5]. The use of non-immersive VR has demonstrated effectiveness towards a variety of motor outcomes in pediatric rehabilitation [6]. With recent advances in immersive VR interaction abilities and the development of more lightweight and lower cost HMDs, the use of immersive VR has become more attractive in pediatric rehabilitation, as the complete visual immersion may enhance presence [7,8]. Several studies have established the feasibility of using immersive VR in pediatric rehabilitation, and there is preliminary evidence for the effectiveness of immersive VR interventions to promote motor learning outcomes in children with disabilities [5]. While more information about the safety of long-term use in children under 12 years of age is required, recommendations for use with this age group include short periods of use punctuated by frequent breaks [9]. While the integration of immersive VR in clinical practice is in its early stages, a greater understanding of the potential unique advantages of immersive VR as a therapeutic intervention may support efforts at evidence-based integration.

One potential benefit of immersive VR is its potential to achieve a “just-right” task difficulty level during motor rehabilitation. A “just-right” task challenge is “*structured so children are required to persist with and problem solve tasks in order to achieve success, however, they are not so difficult that the child loses interest, gives up, or fails the challenge*” [3]. “Just-right” challenge is an important rehabilitation concept, evident across different disciplines, populations, and functional goals [10]. The concept of “just-right” challenge is associated with the “challenge point framework” developed by Guadagnoli & Lee [11]. The authors theorize that an optimal degree of functional task difficulty for an individual with a specific level of skill will lead to optimal learning conditions, with evidence demonstrating the effectiveness of practice at this ‘challenge point’ to improve motor learning [12]. Related to this framework are efforts to examine psychological factors that influence practice adherence, such as motivation [13].

Therapists working with children who require repeated, long-term rehabilitation interventions may struggle to keep them motivated to engage in the persistent efforts required to improve skills beyond current ability levels [14]. Novel and engaging virtual tasks and environments can help in that regard. In addition, VR applications custom-developed specifically for rehabilitation enable precise task difficulty selection, titrating task parameters to meet individual children’s ability levels more precisely than is possible in the real world. For these reasons, immersive VR may provide an ideal practice modality to target “just-right” challenge during motor skill learning.

Currently, therapists use objective task performance indicators and subjective judgements of a child’s affective state when making difficulty decisions targeting “just-right” challenge. This makes the presence of a therapist necessary to propose “just-right” challenge. Some VR applications use automatic dynamic difficulty algorithms with performance-based decision rules to adjust task difficulty based on performance, in a similar way to the challenge point framework [15,16]. These algorithms are useful in situations where the therapist is not present to contribute clinical judgement, such as in telerehabilitation. However, the therapist brings additional important judgements outside of optimal task difficulty. Since “just-right” challenge depends not only on performance (i.e., how successful the learner is at accomplishing the task) but also on the learner’s *motivation* to persist in their efforts to succeed, it makes sense to consider how children’s cognitive processes can contribute to “just-right” challenge. For example, a task difficulty level that is outside of a child’s abilities might be “just-right” for a child who is motivated to succeed and who enjoys being challenged, while a different child might be discouraged by failure and require a difficulty level closer to their abilities. Having an objective means of measuring proxies of these cognitive processes could supplement performance results in algorithms determining “just-right” challenge in telerehabilitation.

Psychophysiology is defined as the scientific study of the relationship between physiological and cognitive processes [17]. Measuring psychophysiological state in real-time is possible with wearable sensors. Houzangbe et al. [18] present a novel method for quantifying "just-right" challenge in immersive VR based on psychophysiological data and performance variables. The authors outline the potential variables of interest and present hypothesized thresholds for "just-right" challenge. Wearable sensors are an active research area in pediatric population, mainly explored for measuring activity level and movement for physical rehabilitation [19]. However, multiple barriers still limit their usage [20,21], including difficulty with placement of adult-sized sensors, and movement artifact during intense activities. Very little research has been done on the use of physiological sensor wearables (e.g. heart rate, electroencephalography) with pediatric populations. Existing studies are conducted in a static condition [22], or are missing details about the potential impact of movement artifact on data integrity [23]. More evidence is required to understand potential data loss and data quality issues in wearable sensors when children undertake movement-based tasks [24]. The protocol described in this paper for this pilot study is focused on the feasibility of detecting variation in psychophysiological states in children during a new motor learning task in immersive VR. As such, it is centered around capturing objectively differing difficulty levels rather than identifying a "just-right" challenge. The study is the first is a step in a larger long-term research goal to train machine learning models to identify "just-right" challenge based on task performance and psychophysiological data. Although the interest of this study is in "just-right" challenge during motor skill learning in children with motor impairments, typically developing children are included in this pilot study to capture a wider range of performance abilities in immersive VR.

Objectives and hypotheses

Objective 1: Evaluate the performance of a) the electrodermal activity (EDA) and heartrate sensor and 2) electroencephalography (EEG) 13-lead sensor in children undertaking a new motor learning task in immersive VR.

Hypothesis 1.1: Data loss will be less than 10%.

Hypothesis 2.2: 70% of collected data will meet pre-determined thresholds for data quality.

Objective 2: Evaluate changes in physiological data at three immersive VR task difficulty levels.

Hypothesis 2.1: EDA number of peaks per minutes, heartrate, level of engagement, cognitive workload and concentration measured through EEG, average time of eye pursuit of the interactable objects, and average number of eye blink per minutes will differ between difficulty levels.

Objective 3: Explore the relationship between physiological data, task performance, and self-reported measures of engagement, cognitive workload, physical effort, and attention/focus at each task difficulty level.

Hypothesis 3.1: Self-report ratings will correlate positively with their corresponding physiological data at each of the three difficulty levels. Specifically:

- EEG engagement index will positively correlate with the self-reported engagement score.
- EEG cognitive workload will positively correlate with the self-reported cognitive workload score.
- EEG concentration and average time of eye pursuit data will positively correlate with the self-reported concentration score. Average blink rate will negatively correlate with the self-reported concentration score.
- Physical activity measured through acceleration data will positively correlate with self-reported physical effort score.

Hypothesis 3.2: Levels of arousal, measured through heart rate (HR) and EDA data, will correlate negatively with task performance.

Material and Methods

Ethical considerations

This research project has been approved by the Research Ethics Board of the Sainte-Justine University Hospital Research Center (2022-3881). We will send the informed consent form via email to potential participants; signing will occur at the study session after providing the opportunity to ask questions. The informed consent document explains why participants are invited to participate, the purpose of the project, the number of participants involved, and the age range. Finally, there is an optional section allowing participants to choose whether they agree to the secondary usage of their data for future research and whether their data will be made available.

Privacy and confidentiality protection

Participant data will be deidentified using codes, and only the research team will have access to the code linking participants' information to the collected data. On the informed consent form, parents have the option to grant permission for the use of deidentified images and videos of the participants for scientific communication and training purposes.

Setting

Data collection will take place at the Technopôle for Pediatric Rehabilitation of the Marie Enfant children's Readaptation Center (CRME) of the Sainte-Justine University Hospital Center in Montréal, Canada.
Study design: Repeated measure within-participant experimental design.

Participants:

Inclusion and exclusion criteria

Fifteen typically developing children aged between 8 and 16 will be invited to participate. Inclusion criteria are cognitive, visual, and auditory abilities necessary to follow instructions and interact with the VR task. Exclusion criteria are photosensitive seizures, visuospatial deficiencies, and known cardiac problems. Interested participants will complete the cybersickness susceptibility questionnaire's non-time sensitive questions [25]. Since the experiment is performed seated, and the virtual environment does not move independently of head movements, there is a limited risk of cybersickness. Children displaying four or more (out of 18 total) indicators of susceptibility to cybersickness (any "yes" answer in the yes-no questions and any rating of 1 in the Likert scales) will be excluded from participation.
Recruitment: Typically developing children will be recruited through social media advertisements. Participants and their parents will provide assent and consent, respectively. This research has been approved by the research ethics review board of the CHU Sainte-Justine (2022-3881).

Sample size calculation

This pilot study is not powered for effectiveness. For the analysis of repeated measure correlations, using the method developed by Bakdash and Marusich [26], with a presumed strong effect of task difficulty, 3 data points (the three different levels of difficulty), 15 participants in total are sufficient to reach a power of 0.80. This pilot study will determine the effect size to power a subsequent larger data collection.

Novel motor learning task in immersive VR: *Ball bounce*

Ball bounce is a custom-developed unimanual task built in Unity3D that requires the player to consecutively bounce a virtual ball on a virtual paddle. The task takes place in a fantasy environment composed of floating islands and castles. The VR controller is represented in the virtual environment by a paddle. Figure 1a: The virtual environment. Figure 1b: the participant's view. The user views a ping-pong-sized ball hovering directly in front of them at their eye level. The ball is dropped after a countdown started when the user squeezes the controller trigger finger. When the paddle enters in contact with the ball then the ball will bounce according to regular physics reaction. If the ball hits the ground, it disintegrates, and a new ball is generated and appears at eye level of the player at its initial position. A trial is started when a new ball is generated and starts falling. The trial ends when the ball hits the floor, automatically triggering a new ball to appear. Consecutive ball bounces during each trial are counted in the score board and the highest number of bounces is displayed.
Task difficulty is modulated through Unity's physics engine global gravity parameter. The ball is coded as a physical object and gravity modulates its speed. There are ten difficulty levels, ranging from 10 percent of real-life gravity to 100 percent of real-life gravity; each progressive difficulty level has a 10% step increase. The virtual environment does not change across difficulty levels. The impact of gravity manipulation on perceived task difficulty was confirmed through preliminary testing with 5 typically developing children.

Figure 1a: The virtual environment. Figure 1b: the participant's view.

Study Procedures

Figure 2 outlines the study protocol. After completing a study demographic form the participant is outfitted with the HMD and the data collection devices.

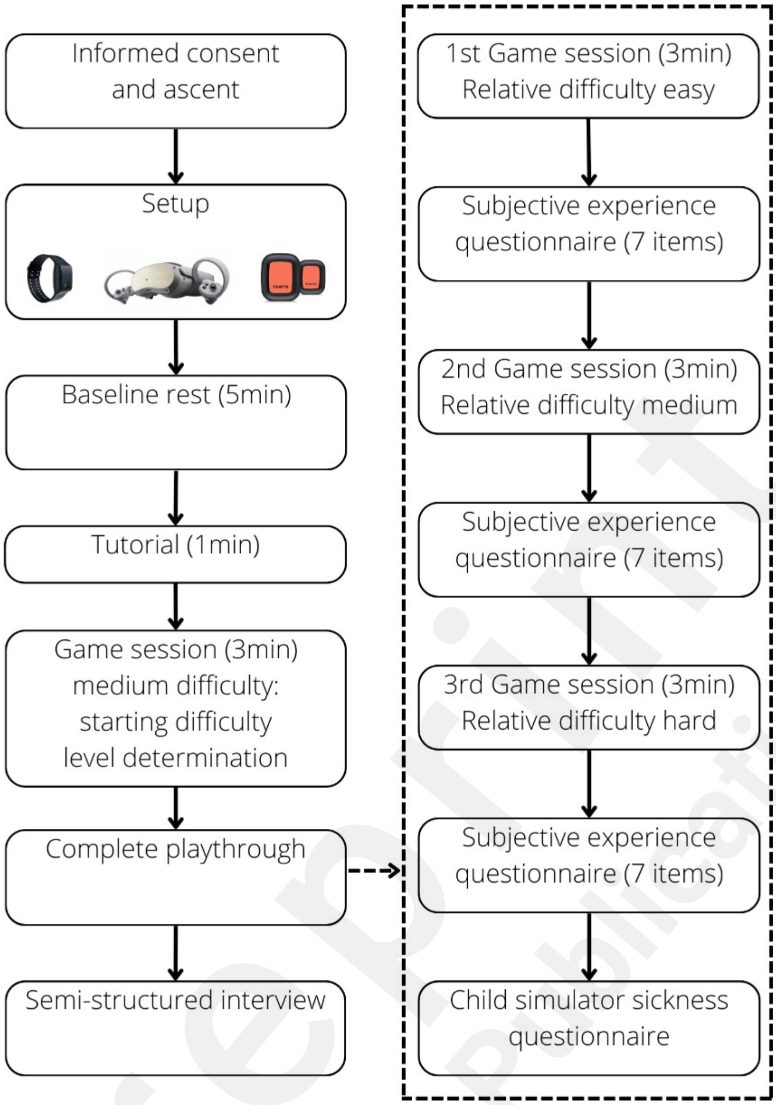


Figure 2. Overview of the data collection protocol.

Participants will be asked to sit still for five minutes to calculate baseline resting state data. They will then receive task instructions Participants play with their dominant hand. All participants are asked to limit the movements of the non-task hand. Participants will first complete a one-minute tutorial to familiarize them with the environment and the gameplay. The tutorial is set at the minimal level of difficulty (gravity is set to 10 percent of its real value). When participants are ready, they can click any button on the controller to start the game.

Participants will play for three minutes at the medium level of difficulty (gravity set to 50%) to evaluate their baseline task abilities. Depending on the participant's performance during this baseline session, the starting difficulty will be set at a very easy level, an easy level, or a medium level. This personalization optimizes task difficulty progression to participant abilities. Visual representation of the difficulty selection and evolution is detailed in Figure 3. Participants then complete 3 three-minute game play sessions at progressively challenging gravity manipulation levels, with breaks between sessions. This number of game play sessions was chosen to limit the effects of fatigue. We chose not to counterbalance task difficulty presentation in order to better reflect real-world task learning conditions in which instructors increase task difficulty parameters as performance improves.

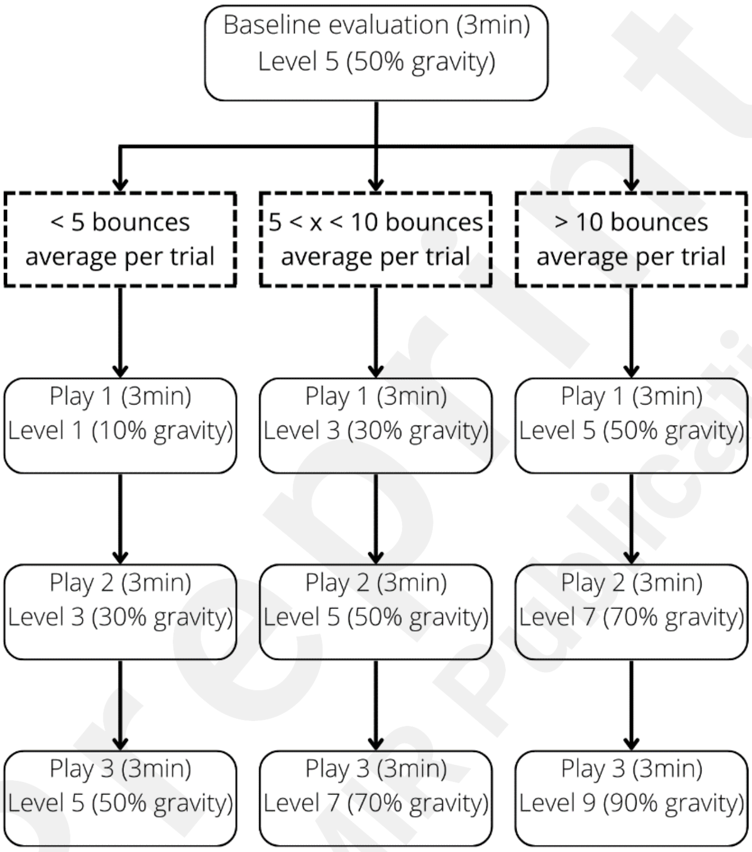


Figure 3: Difficulty selection and progression depending on baseline evaluation.

After each three-minute play session, the participant removes the HMD and answers a study-specific questionnaire asking them to rate agreement with seven statements (one statement per construct) about their engagement, attention/focus, cognitive workload, physical effort, self-efficacy, and motivation. Statements are presented on a 7-item Likert scale with anchors on “strongly disagree” and “strongly agree”.

- Engagement: Two questions inspired from the ITC-Sense Of Presence Inventory [27]) whose scores are averaged:
  - I enjoyed myself during this level.
  - I felt involved in the displayed environment.
- Attention/Focus: I am completely focused on the task at hand (question derived from the Flow Short Scale [28]).
- Cognitive workload: During the task I did a lot of thinking and figuring out (question derived from the revised NASA TLX for children [29]).
- Physical effort: During the task I had to do a lot of physical effort (question derived from the revised NASA TLX for children [29]).

- Self-efficacy: I think I can do well at a more difficult level.
- Motivation: I wanted to work harder to improve my performance / I tried hard to improve my performance (question derived from the Pediatric Motivation Scale [30])

The resting period between each three-minutes play session is between 3-5 minutes, and participants can request a longer break as needed. At the end of the session, participants complete the Child Simulator Sickness Questionnaire [31]. Participants will receive a 25$ (CAD) gift card as a token of appreciation for their participation in the study.

Data collection instruments

Task performance: Participants will wear a Pico 4 Enterprise HMD. Performance data is collected within the Unity task: for each trial, the position of the paddle when the ball hits it and the maximum elevation of the ball after each hit is captured. The number of consecutive hits is calculated. To be considered as a valid bounce the ball must reach a height of at least 15 centimeters. Task performance is defined as the ratio of error over the total number of bounces attempted (Number of error / (number of bounces + number of errors)) during the three-minute trial.
EEG: A Kaptics (Corporation, Montréal QC, www.kaptics.com) EEG with 12 Ag/AgCl dry electrodes is integrated into the Pico4 headgear. The electrodes are placed in the following configuration: Fp1, Fp2, AFz (bias), F3, Fz, F4, C3, Cz (reference), C4, O1, Oz, O2. The Kaptics custom-developed application computes the following psychophysiological metrics:

a. Mental engagement level, measured with the engagement index, which is calculated through Beta and Alpha bands, based on the work of Coelli et al. [32].
b. Cognitive workload, which is calculated through changes in Theta and Alpha bands, based on the work of Di Flumeri et al. [33] and Zammouri et al. [34].
c. Concentration, which is measured through changes in Beta bands, based on the work of Lim et al. [35].

Eye-tracking: The Pico Neo 4 Enterprise has an integrated Tobii eye tracker. Oculometry correlates with attention to a task [36]. The average time per trial of eye pursuit of the ball will be used as a metric of focused attention. Eye pursuit will be computed as the amount of time, when performing the VR task, during which the direction of the eyes intersects with the areas of interests (volumes englobing respectively the ball and the paddle).
A lower blink rate will be indicative of a higher focused attention [36].
Movement quantity: The continuous position of the virtual paddle in the virtual environment is saved at a framerate of 60Hz. From the consecutive three-dimension positions recorded, the total amount of displacement will be computed to get the total amount of motion during the virtual task.
EDA and HR: Participants will wear an Empatica E4 sensor equipped with a photoplethysmography (PPG) sensor and an EDA sensor. EDA, a recognized marker of arousal [37], will be computed as the average number of peaks per minute for each three-minute play period using pyEDA, an open-source python toolkit [38]. Heartrate is also a proxy for arousal [37]. Heartrate in beats per minute will be averaged over each game play. The changes in level of arousal will be computed to determine the intensity of the physiological response, with an optimal level of engagement arousal should be average [37], if it is too high it can be interpreted as a sign of frustration.
Upper extremity movement quality: As an exploratory measure, participants will wear XSens DOT inertial measurement units (IMUs) on the active forearm and on the chest to capture upper limb movement smoothness. Movement smoothness is measured through acceleration data. Less-smooth movements are characterized by fluctuations in velocity, causing local maxima in the velocity profile. It is classified as an acceleration metric since the calculation of this metric is in the acceleration domain [39]. The lower the number of local maxima recorded the smoother the movement is. The average number of local maxima per minute will be computed as an exploratory

measure to look for differences in movement at the different levels of difficulty.

Data processing

Empatica data are stored in the smartwatch during the experiment and then downloaded to a computer for analysis. EDA data will be filtered using a low pass Butterworth filter (frequency of 1Hz and order of six). EEG signals processed by Kaptics are filtered using a band-pass filter between 0.5 and 45Hz and then zero-mean normalized. Kaptics uses the subspace reconstruction method to remove motion artifacts [40].

Analyses

Quantitative statistical analyses will be performed using SPSS for ANOVA, correlations and graphical output and R for the usage of the repeated measure correlation (rmcorr) package [26]. Confidence level will be set at 95%. Descriptive statistics will be presented as counts, means and standard differences by level of difficulty. Demographic categorial data will be presented as means and standard differences by (age), gender and GMFCS level.

Objective 1: Evaluate the performance of the physiological sensors in children undertaking a new motor learning task in immersive VR.

A) Identify Data loss. The acceptable data loss threshold per measure will be set as 10% of total data collection time for each of the three game play sessions. The expected output of data differs by sensor according to frequency. The amount of recorded data, for each three-minute level, over expected output will be computed to measure percentage of data loss.
   a. EDA: Empatica frequency is 4Hz.
   b. Heart rate: Empatica HR value frequency is 1Hz.
   c. Eye-tracking: data will be collected at a fixed frequency (60Hz). When the HMD is unable to accurately detect the eyes of the participants, the values are reported as 0.

B) Data quality: For each three-minute level, the amount of aberrant data will be computed for each sensor. The percentage of aberrant data over the total amount of collected data will then be computed.
   a. EDA: Quality of EDA data is assessed following two criteria [41]: 1) The total range of valid EDA data is 0.05 - 60 µS. Data outside this range will be considered aberrant; 2) An EDA change of more than ±10 µS/sec between any 2 consecutive values is considered aberrant.
   b. Heart rate: The minimal valid value of heart rate data is 60 beats per minute [42], while the estimated maximum valid value is 194 beats per minute [43]. Data outside this threshold will be considered aberrant. Changes in heart rate between any 2 consecutive values superior to ±3 beats per second will be considered aberrant [44].

Objective 2: Evaluate changes in physiological data at three immersive VR task difficulty levels.
To examine intra-individual changes in averaged physiological data at baseline and the three difficulty levels, a repeated measure analysis of variance (ANOVA) will be performed for each dependent variable, with the level of difficulty as the within-subject factor. Sensitivity analysis will be done using the Friedman test, due to the small sample size. Eta squared will be reported as the measure of effect size.
Objective 3: Explore the relationship between physiological data, task performance, and self-reported measures of engagement, cognitive workload, physical effort, and attention/focus at each task difficulty level.
To determine the intra-individual relationship between physiological data and self-reported data, the Pearson product-moment correlation and the Spearman rank correlation will be performed, to explore linear and monotonic relationships. The complete correlation matrix will be reported (with

correlation coefficient as effect sizes and p-values). At each difficulty level, correlations will be explored between:

- the level of engagement computed from the EEG data and the averaged self-reported score of engagement.
- the level of attention computed from the EEG data and the self-reported score of attention.
- the level of attention computed from the eye tracking data (time of pursuit and average blink rate) and the self-reported score of attention.
- the level of cognitive workload computed from the EEG data and the self-reported score of cognitive workload.
- the average amount of movement of the virtual paddle and the self-reported score of physical effort.

Testing to evaluate parallel slopes between conditions will be undertaken [45]. If parallel slopes are identified, then a repeated measure correlation (rmcorr) will be performed [26]. The rmcorr method can handle repeated measures data without violating independence assumptions nor averaging data. It is ideally suited to assess association in intra-individual relationship between paired measures. Visual analysis [46] as well as statistical inference (regression coefficients and p-values) will be reported. We will report visual analyses as well as statistical inference (regression coefficients and p-values) results.

Results

Study recruitment is underway.

Discussion

Targeting "just-right" task challenge during rehabilitation interventions is anchored in evidence-based motor learning principles [3]. Wearable sensors can enable objective measurement of psychophysiological states related to difficulty progression during motor skill learning. A better understanding of wearable sensor task performance during movement-based tasks in children is required [24]. The current state of knowledge on wearable sensor use in pediatric rehabilitation is limited to inertial measurement units and accelerometers [19]. Very few studies have explored the potential of wearable physiological sensors to understand children's engagement during virtual reality-based interactions [22].

This study will evaluate relationships between physiological data and children's self-report during practice of a novel motor learning task in immersive VR. at different task difficulty levels. Findings from this pilot study will inform subsequent work, which could include collecting physiological and self-report data with a child with motor impairment who progress at their own pace through task difficulty levels in immersive VR and asking children to self-identify when they perceive challenge to be "just-right". If objective and subjective data are correlated, this training data could be used to build a machine learning model to predict "just-right" challenge based on the combination of thresholds of different variables, using the subjective self-report of "just-right" challenge to correctly label the corresponding physiological data. As proposed in Houzangbe et al. [18], combining the success rate of a task with psychophysiological levels of engagement, arousal, cognitive workload, and attention could lead to objective identification of conditions necessary to reaching personalized "just-right" challenge. In the longer term, embedding this model within immersive VR motor learning tasks may enable real-time decision-making about task difficulty level to achieve and maintain "just-right" task challenge. Subsequent work can also compare different types of VR tasks to assess the reproducibility of the results and their generalization.

Potential limitations

The small sample size of this pilot study limits the scope of the conclusions. Results will inform calculation of the effect size required to power subsequent data collection. Using commercial physiological wearable sensors may lead to more compromised data quality as compared to medical grade equipment. This limitation is balanced by cost and accessibility benefits. Choosing not to counterbalance task difficulty presentation introduces potential learning or fatigue effects. Using short house-made motivation and focus questionnaires is required as longer validated questionnaires are impractical following short game play sessions.

Conclusions

This is the first step in a program of research exploring factors influencing children's user experiences during motor skill learning in immersive VR. Immersive VR hardware and software are rapidly developing and lowering in cost, increasing their potential as an accessible telerehabilitation modality. If the difficulty of immersive VR tasks can be adapted to "just-right" challenge in the absence of therapeutic decision-making, they may be evidence-based, accessible, and personalized telerehabilitation interventions. Being able to identify, quantify and predict "just-right" challenge can contribute to a future of precision rehabilitation [19] where VR, physiological sensors, and AI models can provide personalized interventions in clinic and home-based contexts.

Acknowledgements

Authors would like to thank the *Regroupement INTER (Ingénieries de technologies interactives en readaptation)* and the *REPAR (Réseau Provincial de Recherche en Adaptation-Réadaptation)* for funding this work. Danielle Levac is supported by a J2 Scholar award from the *Fonds de Recherche du Québec – Santé.*

Data Availability

Completely anonymized data will be made available on public sharing platforms, only for the families that have agreed to share their data.

Authors' contributions

All authors contributed to the design of the study protocol. SH wrote the first draft of the manuscript and all authors contributed to the subsequent versions. SH developed and integrated the data collection tools from the VR software.

Conflict of interest

None declared.

Abbreviations

EDA: Electrodermal Activity
EEG: Electroencephalography
HMD: Head-Mounted Display
HR: Heart Rate
RMCORR: Repeated measure correlation
VR: Virtual Reality

References

1. Fusco A, Tieri G. Challenges and Perspectives for Clinical Applications of Immersive and Non-Immersive Virtual Reality. J Clin Med Multidisciplinary Digital Publishing Institute; 2022 Jan;11(15):4540. doi: 10.3390/jcm11154540

2. Weiss PL, Keshner EA, Levin MF, editors. Virtual Reality for Physical and Motor Rehabilitation. New York, NY: Springer; 2014. doi: 10.1007/978-1-4939-0968-1ISBN:978-1-4939-0967-4

3. Levac DE, Sveistrup H. Motor Learning and Virtual Reality. In: Weiss PL (Tamar), Keshner EA, Levin MF, editors. Virtual Real Phys Mot Rehabil New York, NY: Springer; 2014. p. 25–46. doi: 10.1007/978-1-4939-0968-1_3

4. Holt CJ, McKay CD, Truong LK, Le CY, Gross DP, Whittaker JL. Sticking to It: A Scoping Review of Adherence to Exercise Therapy Interventions in Children and Adolescents With Musculoskeletal Conditions. J Orthop Sports Phys Ther Journal of Orthopaedic & Sports Physical Therapy; 2020 Sep;50(9):503–515. doi: 10.2519/jospt.2020.9715

5. Demers M, Fung K, Subramanian SK, Lemay M, Robert MT. Integration of Motor Learning Principles Into Virtual Reality Interventions for Individuals With Cerebral Palsy: Systematic Review. JMIR Serious Games 2021 Apr 7;9(2):e23822. doi: 10.2196/23822

6. Vieira C, Ferreira da Silva Pais-Vieira C, Novais J, Perrotta A. Serious Game Design and Clinical Improvement in Physical Rehabilitation: Systematic Review. JMIR Serious Games 2021 Sep 23;9(3):e20066. PMID:34554102

7. Villani D, Riva F, Riva G. New technologies for relaxation: The role of presence. Int J Stress Manag US: Educational Publishing Foundation; 2007;14(3):260–274. doi: 10.1037/1072-5245.14.3.260

8. Riva G, Mantovani F, Gaggioli A. Presence and rehabilitation: toward second-generation virtual reality applications in neuropsychology. J NeuroEngineering Rehabil 2004 Dec 8;1(1):9. doi: 10.1186/1743-0003-1-9

9. Kaimara P, Oikonomou A, Deliyannis I. Could virtual reality applications pose real risks to children and adolescents? A systematic review of ethical issues and concerns. Virtual Real 2022 Jun 1;26(2):697–735. doi: 10.1007/s10055-021-00563-w

10. Poulsen AA, Rodger S, Ziviani JM. Understanding children’s motivation from a self-determination theoretical perspective: Implications for practice. Aust Occup Ther J 2006;53(2):78–86. doi: https://doi.org/10.1111/j.1440-1630.2006.00569.x

11. Guadagnoli MA, Lee TD. Challenge Point: A Framework for Conceptualizing the Effects of Various Practice Conditions in Motor Learning. J Mot Behav Routledge; 2004 Jul 1;36(2):212–224. PMID:15130871

12. Ashouri S, Letafatkar A, Thomas AC, Yaali R, Kalantari M. The challenge point framework to improve stepping reaction and balance in children with hemiplegic cerebral palsy: A case series study. J Pediatr Rehabil Med IOS Press; 2023 Jan 1;16(1):37–48. doi: 10.3233/PRM-201522

13. Hodges NJ, Lohse KR. An extended challenge-based framework for practice design in sports coaching. J Sports Sci Routledge; 2022 Apr 3;40(7):754–768. PMID:35019816

14. Chiarello LA, Palisano RJ, Avery L, Hanna S. Longitudinal Trajectories and Reference Percentiles for Participation in Family and Recreational Activities of Children with Cerebral Palsy. Phys Occup Ther Pediatr Taylor & Francis; 2021 Jan 2;41(1):18–37. PMID:32363980

15. Valencia Y, Majin J, Guzmán D, Londoño J. Dynamic Difficulty Adjustment in Virtual Reality Applications for Upper Limb Rehabilitation. 2018 IEEE 2nd Colomb Conf Robot Autom CCRA 2018. p. 1–6. doi: 10.1109/CCRA.2018.8588126

16. Huber T, Mertes S, Rangelova S, Flutura S, André E. Dynamic Difficulty Adjustment in Virtual Reality Exergames through Experience-driven Procedural Content Generation. 2021 IEEE Symp Ser Comput Intell SSCI 2021. p. 1–8. doi: 10.1109/SSCI50451.2021.9660086

17. Browne TG. Biofeedback and Neurofeedback. In: Friedman HS, editor. Encycl Ment Health Second Ed Oxford: Academic Press; 2016. p. 170–177. doi: 10.1016/B978-0-12-397045-9.00121-X

18. Houzangbe S, Zejli Y, Lemay M, Levac D. Quantifying individual and contextual factors that contribute to just-right challenge in an immersive virtual reality pediatric rehabilitation task: a protocol. 2023.

19. Lang CE, Barth J, Holleran CL, Konrad JD, Bland MD. Implementation of Wearable Sensing Technology for Movement: Pushing Forward into the Routine Physical Rehabilitation Care Field. Sensors 2020 Oct 10;20(20):5744. PMID:33050368

20. Lobo MA, Hall ML, Greenspan B, Rohloff P, Prosser LA, Smith BA. Wearables for Pediatric Rehabilitation: How to Optimally Design and Use Products to Meet the Needs of Users. Phys Ther 2019 Jun 1;99(6):647–657. PMID:30810741

21. Louie DR, Bird M-L, Menon C, Eng JJ. Perspectives on the prospective development of stroke-specific lower extremity wearable monitoring technology: a qualitative focus group study with physical therapists and individuals with stroke. J NeuroEngineering Rehabil 2020 Feb 25;17(1):31. doi: 10.1186/s12984-020-00666-6

22. Apicella A, Arpaia P, Giugliano S, Mastrati G, Moccaldi N. High-wearable EEG-based transducer for engagement detection in pediatric rehabilitation. Brain-Comput Interfaces Taylor & Francis; 2022 Jul 3;9(3):129–139. doi: 10.1080/2326263X.2021.2015149

23. Vaughn J, Gollarahalli S, Shaw RJ, Docherty S, Yang Q, Malhotra C, Summers-Goeckerman E, Shah N. Mobile Health Technology for Pediatric Symptom Monitoring: A Feasibility Study. Nurs Res 2020;69(2):142–148. PMID:31972852

24. Behere SP, Janson CM. Smart Wearables in Pediatric Heart Health. J Pediatr 2023 Feb 1;253:1–7. doi: 10.1016/j.jpeds.2022.08.009

25. Freiwald JP, Göbel Y, Mostajeran F, Steinicke F. The cybersickness susceptibility questionnaire: predicting virtual reality tolerance. Proc Mensch Comput 2020 New York, NY, USA: Association

for Computing Machinery; 2020. p. 115–118. doi: 10.1145/3404983.3410022

26. Bakdash JZ, Marusich LR. Repeated Measures Correlation. Front Psychol 2017;8. Available from: https://www.frontiersin.org/articles/10.3389/fpsyg.2017.00456 [accessed Oct 25, 2023]

27. Lessiter J, Freeman J, Keogh E, Davidoff J. A Cross-Media Presence Questionnaire: The ITC-Sense of Presence Inventory. Presence Teleoperators Virtual Environ 2001 Jun 1;10(3):282–297. doi: 10.1162/105474601300343612

28. Martin AJ, Jackson SA. Brief approaches to assessing task absorption and enhanced subjective experience: Examining 'short' and 'core' flow in diverse performance domains. Motiv Emot 2008 Sep 1;32(3):141–157. doi: 10.1007/s11031-008-9094-0

29. Measuring Sustained Attention and Perceived Workload: A Test With Children - Cynthia Laurie-Rose, Lori M. Curtindale, Meredith Frey, 2017. Available from: https://journals.sagepub.com/doi/10.1177/0018720816684063 [accessed Nov 20, 2023]

30. Tatla SK, Jarus T, Virji-Babul N, Holsti L. The development of the Pediatric Motivation Scale for rehabilitation: Le développement de la « Pediatric Motivation Scale » en réhabilitation. Can J Occup Ther SAGE Publications Inc; 2015 Apr 1;82(2):93–105. doi: 10.1177/0008417414556884

31. Hoeft RM, Vogel J, Bowers CA. Kids Get Sick Too: A Proposed Child Simulator Sickness Questionnaire. Proc Hum Factors Ergon Soc Annu Meet SAGE Publications Inc; 2003 Oct 1;47(20):2137–2141. doi: 10.1177/154193120304702013

32. Coelli S, Sclocco R, Barbieri R, Reni G, Zucca C, Bianchi AM. EEG-based index for engagement level monitoring during sustained attention. 2015 37th Annu Int Conf IEEE Eng Med Biol Soc EMBC 2015. p. 1512–1515. doi: 10.1109/EMBC.2015.7318658

33. Di Flumeri G, Borghini G, Aricò P, Sciaraffa N, Lanzi P, Pozzi S, Vignali V, Lantieri C, Bichicchi A, Simone A, Babiloni F. EEG-Based Mental Workload Neurometric to Evaluate the Impact of Different Traffic and Road Conditions in Real Driving Settings. Front Hum Neurosci 2018;12. Available from: https://www.frontiersin.org/articles/10.3389/fnhum.2018.00509 [accessed Nov 20, 2023]

34. Zammouri A, Chraa-Mesbahi S, Moussa AA, Zerouali S, Sahnoun M, Tairi H, Mahraz AM. Brain waves-based index for workload estimation and mental effort engagement recognition. J Phys Conf Ser IOP Publishing; 2017 Oct;904(1):012008. doi: 10.1088/1742-6596/904/1/012008

35. Lim S, Yeo M, Yoon G. Comparison between Concentration and Immersion Based on EEG Analysis. Sensors 2019 Apr 8;19(7):1669. PMID:30965606

36. Adhanom IB, MacNeilage P, Folmer E. Eye Tracking in Virtual Reality: a Broad Review of Applications and Challenges. Virtual Real 2023 Jun 1;27(2):1481–1505. doi: 10.1007/s10055-022-00738-z

37. Bian Y, Yang C, Gao F, Li H, Zhou S, Li H, Sun X, Meng X. A framework for physiological indicators of flow in VR games: construction and preliminary evaluation. Pers Ubiquitous Comput 2016 Oct 1;20(5):821–832. doi: 10.1007/s00779-016-0953-5

38. Hossein Aqajari SA, Naeini EK, Mehrabadi MA, Labbaf S, Dutt N, Rahmani AM. pyEDA: An Open-Source Python Toolkit for Pre-processing and Feature Extraction of Electrodermal Activity. Procedia Comput Sci 2021 Jan 1;184:99–106. doi: 10.1016/j.procs.2021.03.021

39. Scheltinga BL. Suitable metrics for upper limb movement smoothness during stroke recovery. University of Twente; 2019. Available from: http://essay.utwente.nl/79734/ [accessed Aug 28, 2023]

40. Delorme A, Makeig S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. J Neurosci Methods 2004 Mar 15;134(1):9–21. PMID:15102499

41. Kleckner IR, Jones RM, Wilder-Smith O, Wormwood JB, Akcakaya M, Quigley KS, Lord C, Goodwin MS. Simple, Transparent, and Flexible Automated Quality Assessment Procedures for Ambulatory Electrodermal Activity Data. IEEE Trans Biomed Eng 2018 Jul;65(7):1460–1467. doi: 10.1109/TBME.2017.2758643

42. What is a normal pulse rate? Available from: https://www.bhf.org.uk/informationsupport/heart-matters-magazine/medical/ask-the-experts/pulse-rate [accessed Aug 28, 2023]

43. Verschuren O, Maltais DB, Takken T. The 220-age equation does not predict maximum heart rate in children and adolescents. Dev Med Child Neurol 2011;53(9):861–864. doi: 10.1111/j.1469-8749.2011.03989.x

44. Enewoldsen NM. Analysis of the quality of electrodermal activity and heart rate data recorded in daily life over a period of one week with an E4 wristband. University of Twente; 2016. Available from: http://essay.utwente.nl/70244/ [accessed Aug 28, 2023]

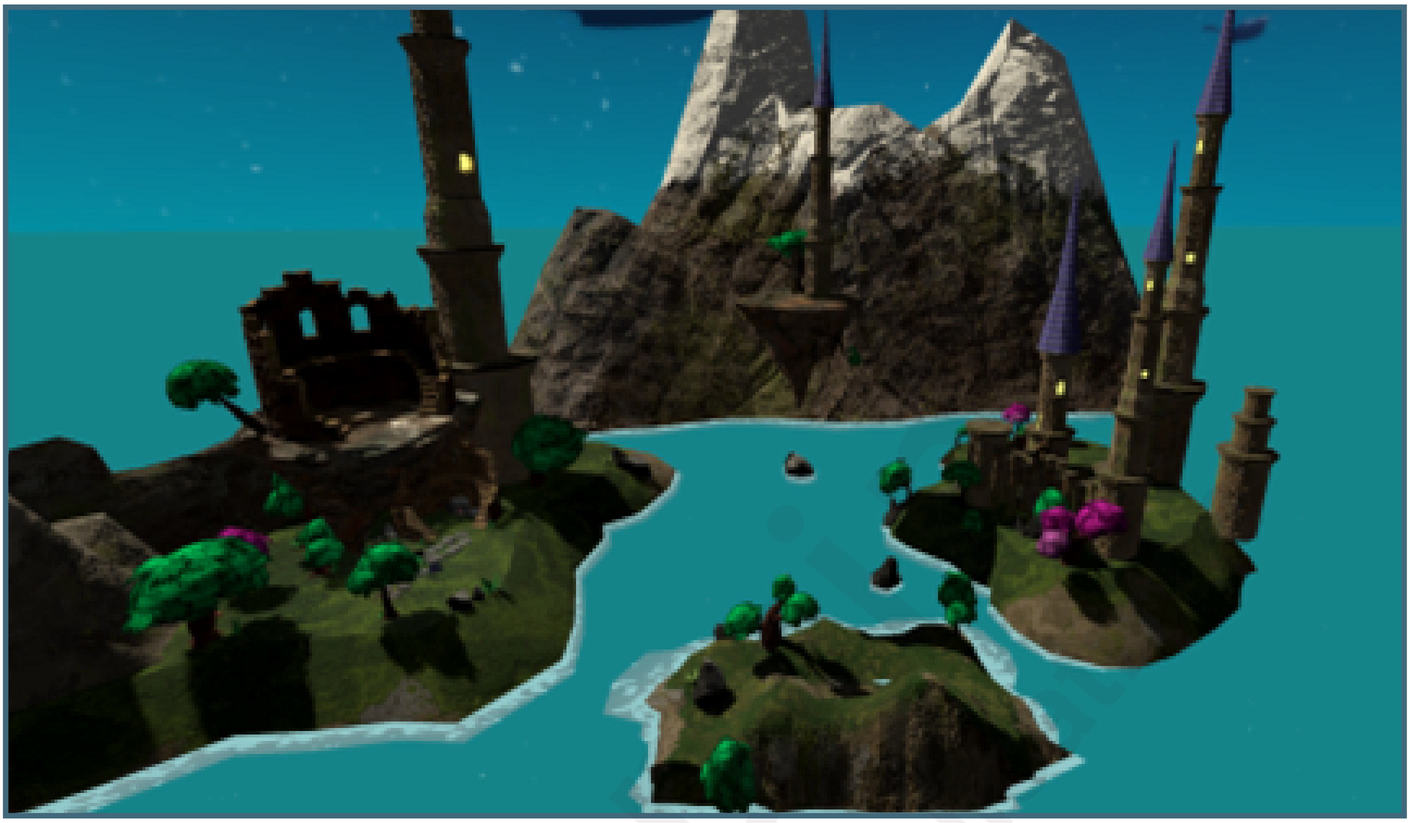
45. Tabachnick B, Fidell L. Using Multivariate Statistics. 7e édition. NY, NY: Pearson; 2018. ISBN:978-0-13-479054-1

46. Tukey J. Exploratory Data Analysis. 1st edition. Reading, Mass.: Pearson; 1977. ISBN:978-0-201-07616-5

Supplementary Files

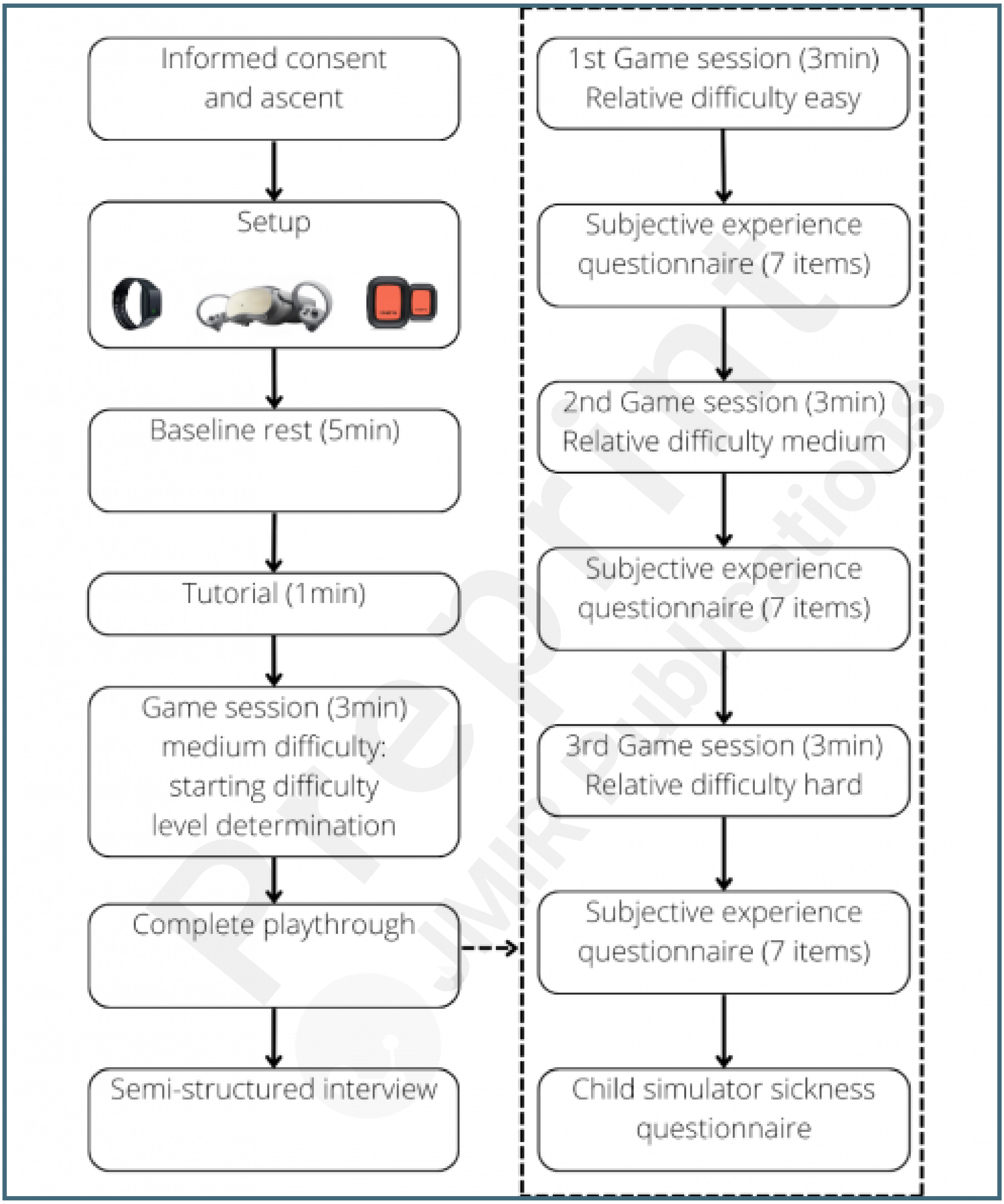
Figures

(a)The virtual environment.



(1b) The participant's view.

Overview of the data collection protocol.



Difficulty selection and progression depending on baseline evaluation.