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ABSTRACT

We present the CREATTIVE3D dataset of human interaction and navigation at road crossings in virtual reality. The dataset has three main breakthroughs: (1) it is the largest dataset of human motion in fully-annotated scenarios (40 hours, 2.6 million poses), (2) it is captured in dynamic 3D scenes with multivariate – gaze, physiology, and motion – data, and (3) it investigates the impact of simulated low-vision conditions using dynamic eye tracking under real walking and simulated walking conditions. Extensive effort has been made to ensure the transparency, usability, and reproducibility of the study and collected data, even under extremely complex study conditions involving 6 degrees of freedom interactions, and multiple sensors. We believe this will allow studies using the same or similar protocols to be comparable to existing study results, and allow a much more fine-grained analysis of individual nuances of user behavior across datasets or study designs. This is what we call a *living contextual dataset*.

Background & Summary

In a joint effort of computer science, cognitive psychology, and clinical practitioners, we aim to analyze the impact that simulated low-vision conditions have on user behavior when navigating complex road crossing scenes: a common daily situation where the difficulty to access and process visual information (e.g., traffic lights, approaching cars) in a timely fashion can lead to serious consequences on a person's safety and well-being. As a secondary objective, we also aim to investigate the potential role virtual reality (VR) could play in rehabilitation and training protocols for low-vision patients.

The experimental protocol consists of three stages: (1) pre-experience preparation including signing the informed consent, a survey and equipping the headset and sensors (2) the experimental study comprised of four conditions: with and without simulated low vision combined with simulated or real walking, six scenarios per condition (in addition to a calibration scenario) with varying interaction complexity and stress levels, two perspective taking tasks in the middle and at the end of a condition, and a short post-condition survey after each condition, and (3) a post-study survey and removal of equipment. The condition and scenario sequence were pseudo-randomized. The entire study lasted roughly two hours.

During the study phase, we fit users with (1) an HTC Vive Pro Eye headset that recorded gaze, head motion, and user interaction logs, (2) an XSens Awinda Starter motion capture system, and (3) Shimmer GSR+ sensors with skin conductance and heart rate capture.

Comparison with similar datasets. A large number of datasets exist for human motion and behavior capture in context. Here we provide a brief comparison in Table 1, focusing on those that have motion capture in context. The most similar dataset to ours is the CIRCLE dataset[1] published very recently, which involved around 10 hours of human motion and egocentric data captured in VR scenes using a 12 Vicon camera setup. The actions concern reaching tasks in scenes annotated with the initial state and goals. For full-body motion capture, the Human3.6m[2] dataset is the most widely used, and up until recently the largest, featuring 3.6 million poses with RGB camera filming as well as actor lidar scans. However, object interactions are not tracked. The focus of Human3.6m to provide a wide variety of human motions by professional actors. The GIMO[3] and EgoBody[4] datasets on the other hand combine motion capture and augmented reality headsets – the Hololens – to capture gaze and motion in context. The physical environments are scanned as 3D meshes and calibrated to have the motion and scene in the same coordinate system. These recent datasets highlight the important role that virtual environments and extended reality (virtual and augmented reality) technologies are already playing for in-context human behavior capture and understanding.

Table 1. Comparison of the dataset with similar existing datasets for 3D human motion capture, primarily with scene context.

Name	Users	Tasks	Scenes	Frames	Context	Modalities
GIMO[3]	11	16	19	129k	point cloud, static	gaze, mocap, egocentric view
CIRCLE[1]	5	128	9	4M	point cloud, static	mocap, egocentric view
Human 3.6M[2]	11	17	N/A	3.6M	None	mocap, RGB camera, lidar
EgoBody[4]	36	13	15	220k	point cloud, static	gaze, mocap, egocentric view
CREATTIVE3D	40	13	6	2.6M	fully annotated, dynamic	gaze, mocap, physiology, logs, surveys

There are a number of datasets that are also worth noting, but not included in the comparison due to the very different nature of their data. The GTA-IM dataset[5] provides synthetic animations generated using the Grand Theft Auto game engine. With the large variety of scenes, character models, and animation styles, the dataset demonstrates the strong potential 3D animations can play in generating realistic simulations for various learning tasks. Another dataset, GazeBaseVR[6] focuses on gaze tracking using VR headsets. Gaze behavior is collected and analyzed for 407 participants on 5 standardized viewing tasks. However, while a headset is employed, the stimuli are 2D.

Contribution. The CREATTIVE3D dataset is for now the largest dataset (in terms of frames, number of subjects, and duration) on human motion in fully-annotated contexts. To our knowledge it is the only one conducted in dynamic and interactive virtual environments, with the rich multivariate indices of behavior as mentioned above. The contribution is twofold. First, we underline the advantages of virtual reality for the study of behavior in context, such as with simulated low vision. Second, we investigate the feasibility of the concept of a *living contextual dataset*: the collection, processing, and analysis of datasets of living behavior in various contexts which aims to be fully reproducible such that future studies using the same protocol can compare to existing results with sufficient confidence. We believe living contextual datasets can be a motor for research questions across multiple domains of modeling, human computer interactions, cognitive science, and society.

Methods

During the study, multiple modalities of data were collected, the setup of which we describe below. Additional details of the study design and system can be found in our previous work[7,8].

Scenarios. In order to build a dataset composed of a large range of user behaviors, six scenarios were designed around two axes of metrics we wanted to observe on the user experience :

- **Cognitive load axis** affected by changing the amount of road lanes and cars driving in the VR environment, ranging from 2 lanes with a car on each, to 1 lane with no car at all.
- **Interaction complexity axis** affected by changing the amount and the type of interactions asked to the player during the scenario, ranging from only one task asking to pick up one object, to multiple tasks of object interaction, object pick up, object placement, traffic light observation.

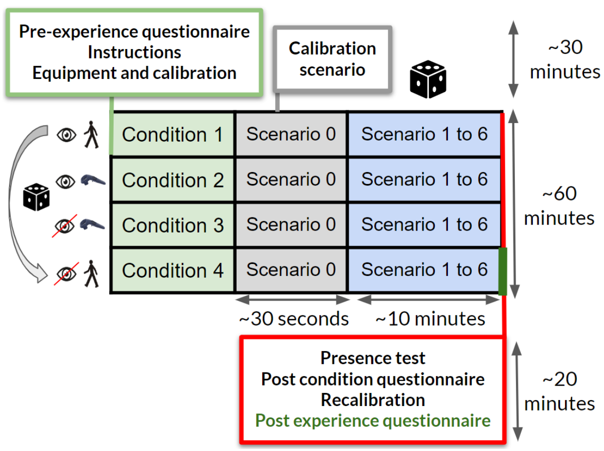
Walking conditions. In each scenario, users did a selection of activities from 13 possibilities: “*Take the trash bag*”, “*Find the key*”, “*Interact with the door using the key*”, “*Go outside*”, “*Press traffic button*”, “*Wait for green light*”, “*Cross the street*” (in two different directions), “*Put the trash bag in the trash can*”, “*Return to house*”, “*Take the box*”, “*Put the box on the table*”, “*Put the box in the trash can*”. The number and choice of activities depended on the cognitive load and interaction complexity axes of the scenario. Each scenario was performed under two movement conditions:

- **Real walking (RW):** the most natural mode of movement in virtual reality. The user walks physically with a 1:1 ratio between the real and virtual distance in the 10 meters by 4 meters tracked space.
- **Simulated walking (SW):** motivated by potential at-home rehabilitation usage where space is limited. The user moves in the direction of the controller by pressing the trigger, leaving the user’s head free to explore the environment. The user can turn on the spot.

Simulating low vision. One of the principal goals of this study was to investigate how low-vision conditions could impact user behavior. Our study targets age-related macular degeneration (a.k.a. AMD) that can result in a scotoma – an area of decreased or lost visual acuity in the center of the visual field – which strongly impacts everyday activities of patients. We take advantage of integrated eye tracking technologies in VR headsets to design a virtual scotoma. Based on existing clinical studies[9], we create a virtual black dot measuring 10°visually, as shown in Figure 1b that follows the cyclopean eye vector (i.e., the combined left and right gaze vectors) from the eye tracker.

Study. With the above setup, the experimental protocol is presented in Figure 1a with each user passing a total of 24 scenarios: six different scenes with a combination of walking (real / simulated) and visual (normal / simulated low vision) conditions. The study was approved by the Université Côte d'Azur ethics committee (N^{o} 2022-057). We recruited 40 participants (20 women and 20 men) through 5 university and laboratory mailing lists. Participants needed to have normal or corrected to normal binocular vision.

The participants upon recruitment were sent a message with their booked time slot, guidelines to wear fitting or light attire, as well as the informed consent. The study lasted approximately two hours long, and was conducted in either English or French at the preference of the participant. 20 euros compensation was given in the form of a check at the end of the study. At the study time, the participants were first invited to sign the informed consent, answer the pre-experience survey, and fitted with the equipment. Participants were informed of the risks of nausea, fatigue, and motion sickness, and were encouraged to ask for a pause or request ending the study if they felt discomfort, which would not impact their compensation. Snacks and drinks were made available to the participant and offered by the experimenters between conditions and at the end of the study.



(a) Study overall workflow with four conditions and six scenarios per condition (in addition to a calibration scene).

(b) Participant view of the simulated scotoma – a region at the center of the visual field with no visual information – following the gaze of the participant. The scotoma represents 10°in diameter of the foveal field of view, based on clinical studies[9].

Figure 1. Overview of the study workflow and simulated low-vision condition with a virtual scotoma

During the study, two experimenters were always present to help arrange the equipment, answer questions, and provide the participant with guidance in using the equipment. When the participant is walking with the headset on, one of the experimenters is always focused on them to notice any loose equipment, check for risk of collision or falling. Inflatable mattresses surround the navigation zone to prevent any collision with walls or equipment.

At the beginning of each condition, a pilot scenario (numbered 0) was presented to the participant to help them discover the environment, familiarize with the interactive and navigational modalities in order to lower the learning curve. This scenario is also used to calibrate the headset height. The calibration was designed after numerous pilot tests that showed a miscalculation of headset height using the Vive's integrated sensors, and also encouraged users to maintain a more upright pose to avoid instability.

Following the pilot scenario, each participant then completed six scenarios under the four conditions, for a total of 24 scenarios. The sequence of the conditions and the sequence of scenarios under each condition were pseudo-randomized using the Latin Square attribution to avoid the effect of repetitive learning and fatigue on specific conditions.

At the end of every three scenarios, participants also performed a pointing task[10], to quantify the level of presence the user experiences in the environment. During this test, the virtual environment is hidden, and the participant is asked to point with their arm in the direction of a target designated by the audio instruction, usually a salient object with which they interacted during the scenario such as a trash can or the initial location of the key or garbage bag. A strong deviation between the participant's arm and the correct direction would indicate a higher level of spatial disorientation, and likely a reduced level of presence.

The post-condition survey was presented to the participant after each condition, which also served as a pause period, to re-calibrate motion tracking, eye tracking, physiological sensors, and give the participants the opportunity to ask any questions and declare sensations of fatigue or nausea. At the end of all conditions, the equipment was removed and the final post-experience survey was presented to the participant.

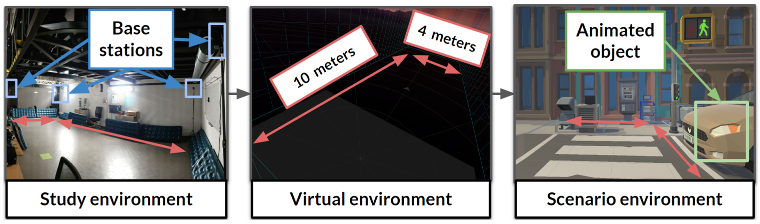


Figure 2. The environment used for the experience measures 4 by 10 meters in navigation area is delimited by four base stations, one at each corner, and aligned with the virtual environment. Mattresses surround the are for security.

Materials and data collection. The study involved various equipment for running the scenarios and capturing user behavior including:

Eye tracking headset with eye tracking being a strong prerequisite for this study, in order to place the virtual scotoma in real time based on the gaze position for the simulated low-vision condition. We chose the HTC Vive Pro Eye, which includes by default eye and head tracking functionality, with SteamVR for the VR environment configuration. We defined the size of the environment based on standard road crossings. The minimum required width of a car lane is $3.5m$, and the minimum width of the pedestrian crosswalk was $2.5m$ with the standard being $4-6m$. We included one meter of pedestrian crossing on each side of a two lane road, and some margin on the sides of the crosswalk to ensure safety. In total, the required navigation space for this study is $10m$ x $4m$, delimited in Figure 2. We used thus used an add-on wireless module to enable such a large navigation space.

Motion capture which provides very rich metrics such as step length or body inclination of participants to evaluate how confident they feel walking in a VR environment. It can also be used such as to validate the accuracy of the pointing task. The MVN Awinda system was chosen in the end due to its resilience towards magnetic interference as well as the precision of the captured data. The Xsens MVN 2022 software was used to calibrate and record the data, and the Xsens MVN motion cloud was used to convert the records in formats *.mvnx* and *.bvh* for later analysis. Users were generally very comfortable with the motion capture equipment, reporting little to no interference with the task in the survey after each condition (from questionnaires, average score of 1.175 over all conditions, 1 indicating no interference and 5 indicating strong interference).

Physiology sensors that can capture the skin conductance (a.k.a. GSR or galvanic skin response) and heart rate, which can be used to measure the level of arousal of the user or the level of activity they are experiencing. The GSR Shimmer solution was chosen in the end for its higher data rate (15Hz re-sampled at 100Hz). The Consensys software was used for the configuration and initial data processing and export. The placement of the sensors was tested repeatedly before the study to find the configuration that interfered least with the task, and also prevented impact of interactions such as pushing the buttons on the controller. In the end, the GSR sensor was placed on the finger roots of the non-dominant hand, and the heart rate sensor on the tip of the thumb. We instructed users on how to hold the controller as to avoid pushing on the sensors. In the end, users did not report significant discomfort when doing interactions with the hand equipped with sensors (from questionnaires, average score of 1.538 over all conditions, 1 indicating no interference and 5 indicating strong interference).

Surveys that we coupled the sensor and log data, proposed during a co-design session with all project members. The surveys were administered at three time points: pre-experience (T1), post-condition (i.e., administered after each of the four conditions), and post-experience (T2). The pre-experience survey comprised: study information (i.e., user ID, study language), demographics (i.e., gender, age group), previous experience with VR and video games, experiences of motion sickness (i.e., usage frequency, open question about identified situations), technology acceptability based on the UTAUT2 model (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and behavioral intention) where the term “mobile Internet” from the original English version and the term “ICT for Health” from the French version were replaced by “virtual reality”[11,12]. The post-condition survey comprised: condition information (i.e., real walk without scotoma, real walk with scotoma, simulated walk without scotoma, simulated walk with scotoma), the NASA task load index[13] (i.e., mental demand, physical demand, temporal demand, performance, effort, frustration), emotion (i.e., positivity and intensity), simulator sickness questionnaire[14] (i.e., two items per dimension: oculomotor-related, disorientation-related, nausea), perception of the experience (7 items created based on the experimental conditions), difficulties encountered during the task and global feedback (open question). The post-experience survey comprised: four items from the presence questionnaire (Witmer & Singer[15]), emotional state (SAM[16]), and technology acceptability (as measured in T1). The full list of items included in the surveys is listed in Tables 5 and 6 in the Appendix.

Data format and machines. All data modalities were labeled with Unix timestamps (except for the surveys). The system logs, gaze plus head tracking were done on a Windows 10 desktop machine with GTX 3080 graphics card while the remaining data – motion capture, physiological sensors, and survey – were collected on a laptop also with a GTX 3080 graphics card. Using the head data on the desktop machine and the motion data with head coordinates on the laptop, we are then able to synchronize the two data streams, as will be described in the next section.

Data Records

Table 2 summarizes all the data modalities, the capture equipment and/or software, and data characteristics.

The data package is contained in a single repository with documentation, tools, a number of usage examples, and data of users 1 to 40.

The structure of the data is as follows:

```
GUsT-3D Data
├── Readme.md
├── Tools (spatial_sync.py) script to spatially synchronize motion data
├── Usage examples
├── Scenarios: scenes as point cloud
└── Data
    ├── questionnaire (.lss .csv): survey content and results
    ├── validation.csv: CSV with all the data issues
    ├── config.json: order of scenes for each participant
    ├── User 1
    │   ├── Condition_RWNV (RW/SW = real/simulated walking; NV/LV = normal/low vision)
    │   │   ├── Scene_SI0V
    │   │   │   ├── U1_RWNV_SC_dataframe.csv, dataframe125Hz.csv: Example dataframe for the user
    │   │   │   ├── U1_RWNV_SC_motion.bvh: Segmented raw motion data
    │   │   │   ├── U1_RWNV_SC_motion_hierarchy.csv, pos.csv, rot.csv: Absolute joint coordinates
    │   │   │   ├── U1_RWNV_SC_motion_transf.json: Transformation matrix for spatial synchronization
    │   │   │   ├── U1_RWNV_SC_shimmer.csv: Shimmer data
    │   │   │   ├── U1_RWNV_SC_LogI.json, U1_RWNV_SC_LogP.json: GUsT-3D system logs
    │   │   │   ├── U1_RWNV_SC_head.json: Gaze tracking - Head data processed
    │   │   │   ├── U1_RWNV_SC_gaze.json: Gaze tracking - Gaze data processed
    │   │   │   ├── U1_RWNV_SC_timesync: Gaze tracking - timesync
    │   │   │   └── U1_RWNV_SC_por.json: calculated points of regard
    │   │   └── Scene_SI2V / CI0V / CI1V / CI2V
    │   └── Condition_RWLV / SWNV / SWLV
    └── User 2, User 3,...User 40
```

Technical Validation

In order to ensure high data quality, multiple validations were put in place, including ten pilot runs preceding the actual study, detailed list of data issues, conducting data synchronization, and verifying the internal consistency of the questionnaires used, measured by Cronbach's alpha[17]. We detail each of these validations below.

Pilot studies. 10 pilot studies were carried out (four women and six men) from researchers and students in the project, from diverse backgrounds of computer science, cognitive science, neuroscience, and sport science. These pilot studies were repeated over a two month period involving iterative improvements to the study, refining of the protocol and surveys, and finally an

Table 2. The collected data modalities, equipment used, format, the logging frequencies, and a brief description.

Type	Equipment	Format	Frequency	Description
System logs	GUsT-3D	.json	10 Hz	objects position, objects state, objects interactive properties, user position, user interaction, current task, objects in user visual field
Physiological sensors	Shimmer GSR+	.csv	EDA 15.9Hz HR 51Hz Resamp. 100Hz	Heart Rate (HR), electrodermal activity (EDA)
Motion capture	XSens Awinda Starter	.csv .bvh	60 Hz	17 sensors for head (1), torso (4: shoulders, hip, and stern), arms and legs (8: upper and lower limb), and feet and hands (4). The .csv files contain the processed absolute joint coordinates calculated from the .bvh file, as well as the transformation matrix to spatially transform the motion data into coordinates of the 3D scene.
Gaze and head tracking	HTC Vive Pro Eye	.json	120 Hz	For left, right, and cyclopean eye (combined gaze vector of both eyes): gaze vector (x,y,z) , pupil size, eye openness percentage, and data validity mask; Head position and rotation vectors
Surveys	LimeSurvey	.json	N/A	Surveys described in Table 5 as well as experimenter observation notes

all-hands co-design session with project members in December 2022 to validate and approve the final version of the study before the official launch in January 2023.

Data issues and transparency. Despite the protocol devised and iterative testing, technical issues can and do occur in complex studies such as the one we carried out, due to accidental manipulations on the experimenter's side, hardware crashes, issues in proprietary software, latency, and individual difficulties for participants – most of which is normal and outside of the control of the study design.

With the objective of being full transparent on the data, we report all the incidents in the production process in a structured way. Specifically, we provide in the data the `validation.csv` file which gives a comprehensive list of various data issues, and their impact. The partial example of a row is shown in Table 3. An empty cell indicates no issues were observed. An X indicates an observed issue at a global level (e.g., incomplete questionnaires due to crash in survey server), or if only a specific number of scenes are impacted, the impacted condition and scene ID are provided.

Table 3. Two example entries of data issues in the `validation.csv` file. For example, the cell in bold indicates that a hardware crash occurred during condition 1 scene 1 due to the wireless module.

UID	Questionnaire (incomplete)	Missing gaze data	Hardware crashes	...
663		SWLV(CI1V)	...	
...	...	...	...	...
592	X		**RWNV(SI0V) - Wireless**	...

Out of the data on 960 scenarios (24 per participant), we observed the following more critical issues that render one datatype unusable for a single scenario of a participant:

- Gaze: missing eye or head data (5 scenarios), inconsistent head coordinates (1 scenario) and timesync (6 scenarios).
- Questionnaire: missing questionnaires in the post-experience survey due to connection problems (8 participants)
- GUsT-3D logs: missing or irregular files (2 scenarios and all data for 2 participants)
- Physiology: oversampling (1 participant), heart rate data not dependable

The missing timesync information can be corrected by applying an average delta of 28000 (28 ms) which will ensure data synchronization with an accuracy of within 6 ms (delta ranged between 22000 and 34000).

Hardware crashes also occurred for seven participants due to the wireless module, impacting maximum one scenario for the participant, mostly at the beginning of the study. The scenario was re-run after a hardware restart and the study continued without further issues.

Temporal and spatial synchronization. As the different modalities of the data were collected through dedicated applications on two separate machines, with different Unix timestamps and 3D axis referential, an important step in pre-processing is data synchronization. This involves temporal synchronization for all modalities of the data, and spatial synchronization of the motion data into the 3D scene referential. The presence of head position and rotation data on both machines – head tracking from the HTC Vive Pro Eye headset on one ($p_H \in \mathbf{R}^3, r_H \in \mathbf{R}^3$), and head point motion capture on the other ($p_M \in \mathbf{R}^3, r_M \in \mathbf{R}^3$)– provides us with a robust means to synchronize the various data streams on the two machines.

To establish temporal synchronization, it becomes imperative to calculate a scalar value that encapsulates this temporal alignment. To achieve this, we employ the computation of velocity, and acceleration magnitude, which characterizes the head's motion within three-dimensional space. The magnitude provides a scalar value describing the head's speed, regardless of its direction.

We first resample p_H to 60Hz, aligned to p_M sampling rate, then take the derivative of the positions to calculate the velocity $|\vec{v}(t_i)|$ for the time point t_i using the Euler distance divided by the frame time $(t_{i+1} - t_i) \approx 16,67ms$:

$|\vec{v}(t_i)| = \sqrt{(x_{t_i+1} - x_{t_i})^2 + (y_{t_i+1} - y_{t_i})^2 + (z_{t_i+1} - z_{t_i})^2} / (t_{i+1} - t_i)$.

However, the magnitude of velocity exhibits significant noise, particularly from the HTC (v_H), which exhibits highly variable and peaky signal characteristics. To mitigate this issue, we employ a two-step approach: compute the 95th percentile of v_H, followed by the application of a Gaussian filter to both velocities v_H and motion capture one v_M. The Gaussian filter smooth out short-term fluctuations and highlight long-term trends, enhancing the velocity quality. Gaussian filter is based on the Gaussian kernel, defined as:

$$G(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{t^2}{2\sigma^2}} \tag{1}$$

where t is the time and σ is the standard deviation of the Gaussian distribution. The Gaussian kernel values are computed for each of the discrete time velocity values using the formula mentioned above. We then convolve the velocity data with the Gaussian kernel, using a discrete convolution operation to apply the Gaussian filter to the velocity profile.

To enhance the smoothness of the head's velocity profile, we aimed for a continuous and seamless motion without sudden changes within a 2-second window, equivalent to 120 frames of our data. To achieve a more refined and localized smoothing effect, we conducted experiments using different kernel sizes, characterized by the Full Width at Half Maximum (FWHM), ranging from 10 to 120 frames, roughly 2.4 times the standard deviation (σ). Based on the observed performance we determined that a FWHM of 94 frames ($\sigma \approx 40$) effectively regulates the level of smoothing for our velocity data preserving essential movement patterns. In addition, the application of Gaussian smoothing to the velocity data prior to derivative computation enhances the reliability of our acceleration estimates.

Once we have the smoothed velocity data (v_{H_s}, v_{M_s}), we compute the acceleration magnitude (a_H, a_M) in a similar manner as a derivative of v. Similar to our approach for velocity, we applied a Gaussian filter to the accelerations using a FWHM of 94 frames, resulting in smoothed acceleration data denoted as (a_{H_s}, a_{M_s}). To achieve temporal synchronization, we employ cross-correlation, which allows us to find the time shift or lag that aligns two datastreams in time. In this context, we work with two sets of data, namely (v_{H_s}, v_{M_s}) for velocities, and (a_{H_s}, a_{M_s}) for accelerations of to the head. As depicted in Figure 3, higher correlation values are observed with the acceleration data. Consequently, we have elected to use acceleration as our reference for temporal synchronization and lag determination. Each scenario was synchronized individually, exclusively under real walking conditions. Subsequently, to establish a robust measure of time lag for each subject, we computed the median of all lags obtained from conditions 1 and 3, encompassing the six scenarios within each condition.

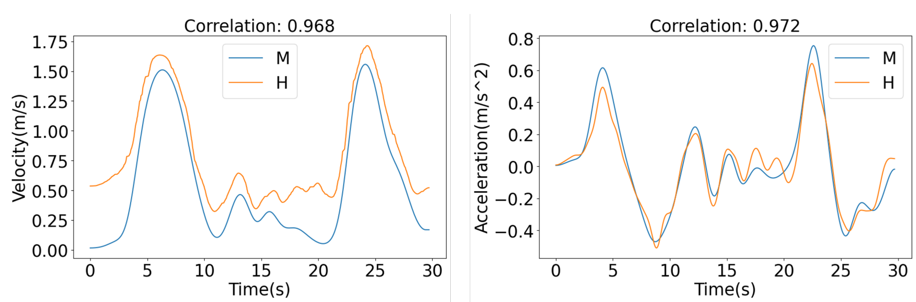
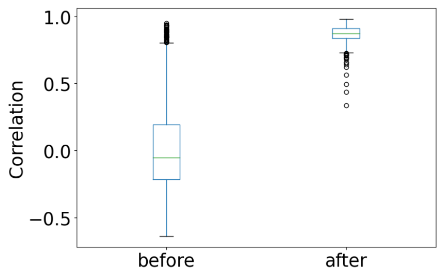
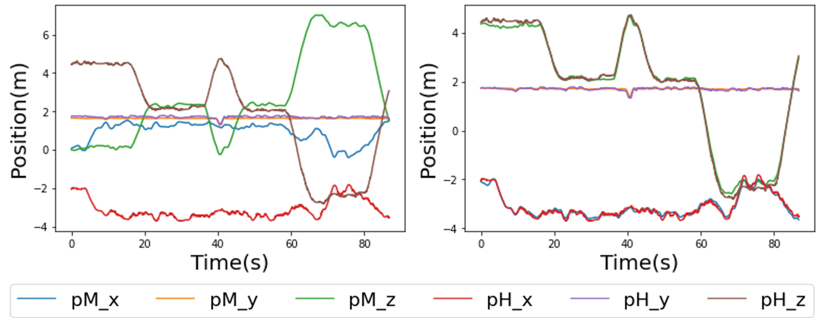


Figure 3. Graphs of velocities (right) and accelerations (left) after temporal synchronization for one scenario, using the head data from the HTC Vive Pro Eye (orange) and head data from the XSens Motion Capture (blue) represented as H and M respectively.

To verify the accuracy of temporal synchronization processes, we conducted correlation analyses for each scenario in all the subjects. Our results consistently yielded correlation coefficients exceeding 0.8 in the majority of cases, indicating robust temporal alignment of our data. Nevertheless, it is worth noting that certain exceptional cases exhibited lower correlation values. These anomalies can be attributed to data inconsistencies, particularly in instances involving data collection from HTC devices.



(a) Cross-correlation values for each scenario before and after synchronization.



(b) Head position for one scenario before (left) spatial synchronization and after (right). HTC and Motion Capture Data Represented as p_H and p_M respectively.

Figure 4. Validation of temporal and spatial synchronization of the two head data streams.

Following temporal synchronization, the next step involves addressing spatial synchronization. This entails the computation of a transformation matrix. To align the two sets of 3D points, denoted as p_H and p_M, representing the positions of the Head obtained from HTC and motion capture, respectively, we employ Procrustes analysis[18]. This method facilitates the determination of the optimal rigid transformation between the point set p_H (referred to as set A) and point set p_M (referred to as set B). As shown in Equations (2)-(6): Set A with n points: $\{A_1, A_2, \ldots, A_n\}$, each represented as (x_i, y_i, z_i) and Set B with m points: $\{B_1, B_2, \ldots, B_m\}$, each represented as (x_i, y_i, z_i). We (1) compute the centroids for both sets, (2) center both sets by subtracting their respective centroids, (3) compute the covariance matrix H, (4) perform Singular Value Decomposition (SVD) on matrix H to derive matrices U, S, and V and obtain the rotation matrix R, (5) compute the translation vector T, and (6) with the derived transformation matrix R and translation vector T, align set A with set B.

$$
\begin{cases}
\overline{A} = \frac{1}{n}\sum_{i=1}^{n} A_i \quad \text{and} \quad \overline{B} = \frac{1}{m}\sum_{i=1}^{m} B_i & (2) \\
A_{c_i} = A_i - \overline{A} \quad \text{and} \quad B_{c_i} = B_i - \overline{B} & (3) \\
H = A_c^T \cdot B_c & (4) \\
R = V \cdot U^T & (5) \\
T = \overline{B} - R \cdot \overline{A} & (6) \\
B_i = R \cdot A_i + T & (7)
\end{cases}
$$

Figure 4b presents the outcomes of the spatial synchronization process. This is evident after the application of the transformation matrix to the motion capture head data denoted as p_M. We provide in our dataset the *spatial_sync.py* script that calculates the transformation matrix *transf.json* from the *motion_pos.csv* and *por.json* file that can be applied to the *motion.bvh* files for visualization. The *motion_pos.csv*, *motion_rot.csv*, and *matrix.json* are the standard input for the GIMO[3] transformer-based architecture.

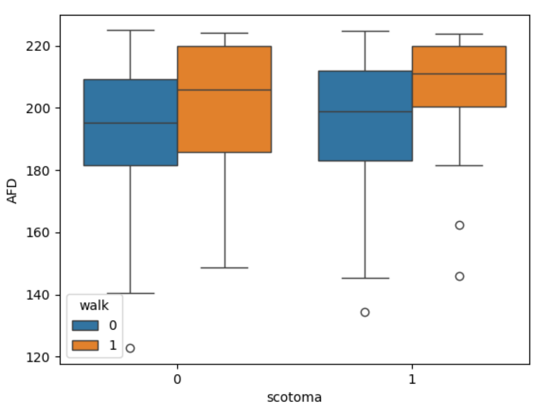
Internal consistency of the questionnaires used. The calculation of Cronbach's alphas was not dissociated between French and English versions regarding the low number of participants in each group (i.e., 15 surveys completed in English and 25 surveys completed in French). Descriptive statistics and Cronbach's alphas of the UTAUT2 and NASA TLX questionnaires are presented in Table 4. The Cronbach's alphas of the UTAUT2 subscales were satisfactory[17], except for the "facilitating conditions" subscale post-experience, which was below the recommended values and should be used with caution in future analyses. The Cronbach's alphas of the NASA Task Load Index were acceptable[17].

Usage Notes

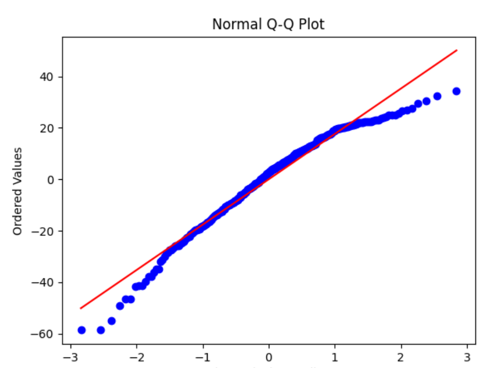
Multivariate dataframe. We provide with the source code the script *ex_dataframe.py* that facilitates the generation of a dataframe with the multivariate gaze, motion, emotion, and user log data for each participant. The resulting dataframe can then be used as input for data visualization, statistical modeling, machine learning, and other applications. A number of these applications are described in more details below.

Table 4. Descriptive statistics and Cronbach's alphas on the UTAUT2 and NASA TLX questionnaires for each of the four conditions. MD% indicates the percentage of missing data due to technical errors.

Scales and subscales	MD %	Mean	SD	Minimum	Maximum	Cronbach alpha
Technology Acceptability - T1						
Performance expectancy	2.5	2.50	1.23	1.00	5.67	0.76
Effort expectancy	2.5	4.87	0.99	2.75	7.00	0.81
Social influence	2.5	2.77	1.66	1.00	7.00	0.86
Facilitating conditions	2.5	4.80	1.47	1.67	7.00	0.64
Hedonic motivation	2.5	5.97	0.83	4.00	7.00	0.73
Price value	2.5	3.89	1.26	1.00	6.67	0.83
Habit	2.5	2.01	1.25	1.00	6.67	0.74
Behavioral intention	2.5	3.81	1.18	2.00	7.00	0.70
Technology Acceptability - T2						
Performance expectancy	20.0	2.54	1.36	1.00	5.67	0.88
Effort expectancy	20.0	5.72	0.86	4.00	7.00	0.84
Social influence	20.0	2.57	1.60	1.00	7.00	0.96
Facilitating conditions	20.0	4.96	1.01	2.67	6.67	0.34
Hedonic motivation	20.0	6.09	0.80	4.67	7.00	0.87
Price value	20.0	3.71	1.28	1.33	6.33	0.86
Habit	20.0	2.25	1.57	1.00	6.67	0.90
Behavioral intention	20.0	3.74	1.36	1.67	7.00	0.75
NASA TLX - RWNV	0.0	3.74	0.91	2.17	5.67	0.52
NASA TLX - RWLV	0.0	3.91	1.24	2.17	7.00	0.72
NASA TLX - SWNV	0.0	3.95	1.13	1.83	3.95	0.63
NASA TLX - SWLV	0.0	4.33	1.26	2.17	4.33	0.58



(a) The whisker plots of the real and simulated walking conditions (blue and orange respectively) with and without the scotoma.



(b) Q-Q plot of the residual for the best model selected

Figure 5. We used a mixed linear model on the residuals of the real and virtual walking on average fixation duration (AFD) and scotoma conditions with the formulation $AFD \sim scotoma + walk + complexity + interactions + (1|participant)$.

Statistical modeling. Beyond calculating the means of various metrics on various study conditions, we can establish models that measure the significance of various factors in our study design. Using the example of motion, suppose we would like to investigate whether the walking condition (real or simulated) impacts various gaze behaviors statistics including average fixation duration (AFD) in milliseconds and percentage of points of regard classified as fixations. We first calculate fixations using a classical I-VT algorithm[19] with a velocity threshold of 120. We apply a mixed linear model of the real and virtual walking with the formulation $AFD \sim scotoma + walk + complexity + interactions + (1|participant)$ which models $participant$ as a random effect and the remaining factors as fixed effects. We did find that there is a significant impact of the walking condition on AFD, with globally longer fixations occurring under the simulated walking condition, while no significance was found between the normal and simulated scotoma conditions. The whisker plots in Figure 5(a) show the distribution of fixation duration for the two walking and scotoma conditions, as well as a validation with a Q-Q plot in Figure 5(b) showing that our model seems to correctly fir the shape of our data distribution. This finding could merit further attention on investigating user attention and its relation to training or rehabilitation efficacy in VR when space is limited, such as when one must replace real navigation modalities with proxies such as joysticks.

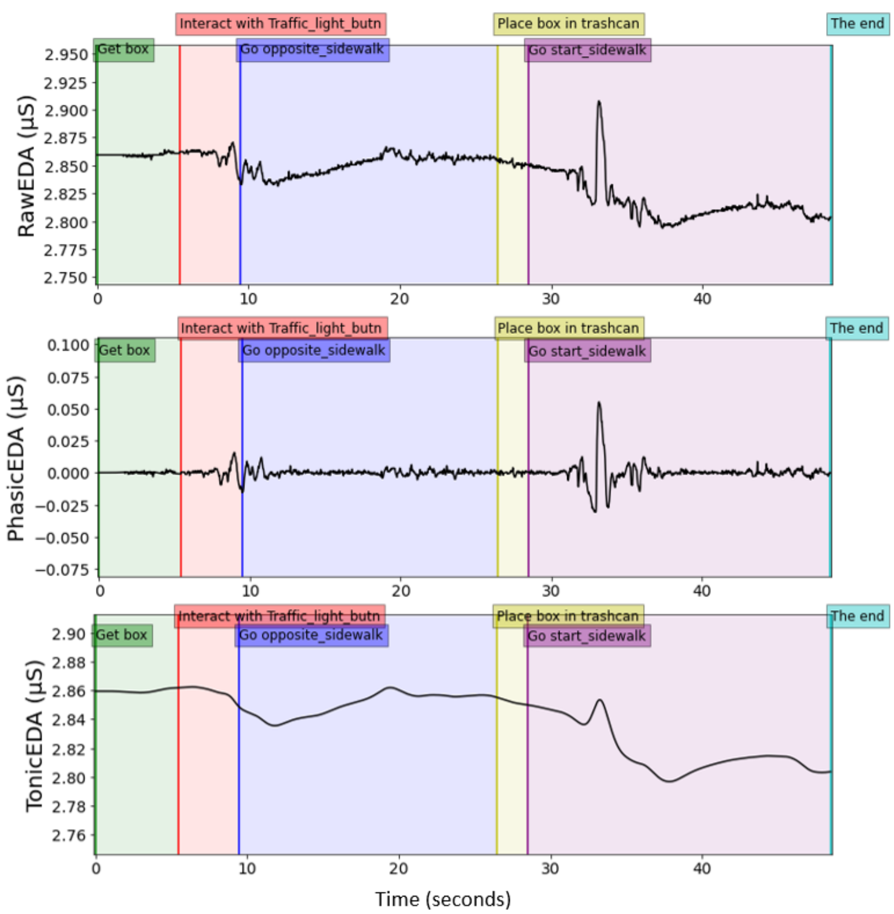


Figure 6. Example evolution of the tonic component for EDA for one user under real walking and normal vision condition with task boundaries indicated by the colored lines. We see a small leap around the moment a car honks at the user for jaywalking.

Fine-grained user understanding. The rich recorded context allows us to have a fine-grained view of the user's current state, both from symbolic and continuous data. We take the example of electrodermal activity (EDA, a.k.a. skin conductance), captured using the Shimmer GSR+ module. Using NeuroKit2[20] we can process the EDA levels to separate the phasic and tonic components: the former is fast-changing and stimulus dependent while the latter is slower to evolve and more continuous. In Figure 6 we show a graph of the evolution of the user's raw EDA and the phasic and tonic components throughout a single scenario. The example script to generate this graph *ex_EDA.py* is included in this package.

Machine learning. The calculated dataframe from *ex_dataframe.ipynb* contains the synchronized, multivariate, spatial-temporal data for each user at 125 Hz, saved in a file $UserID\_condition\_scenario\_dataframe125Hz.csv$. This is naturally a time series that can be used for various machine learning tasks, including:

- *Classification*: binary classification such as between users of two modalities of walking (real or simulated) or presence of (virtual) visual impairment, and multi-class classification such as the current task
- *Time series forecasting*: such as trajectory and motion prediction, or evolution of physiological arousal
- *Salience prediction*: such as accumulated the saliency map of gaze in the 3D scene

We would also like to cast some perspectives beyond these known learning tasks that can be afforded by this dataset, that will allow us to explore the more complex interplay of human behavior with the contextual environment. One such interplay is that between the predictability of gaze based on the level of arousal and salience of visual content, which we explored in previous work and open dataset for 360°videos[21–23], and can be extended to 3D environments with 6 DoF (degrees of freedom).

The dataset introduces additional challenges to machine learning methodologies, most notably where blending structured and unstructured data is concerned. For example, we can investigate approaches that blend the structured contextual logs of interactions and scene entities, with the unstructured video feed of the user's perspective, in order to improve both the accuracy and explainability of the trained model. Another problem is that of multimodal prediction, a dominant subject in multimedia analysis. Advances in the last five years in vision language transformers investigate tasks to match or generate text descriptions from video for example, from which we can imagine tasks on our dataset such as multimodal trajectory prediction for gaze and motion data.

Finally, we would also like to inspire tasks for trajectory prediction and recognition of diverse populations, notably with visual impairment, a prominent focus of our dataset. This task underlines the growing concern of bias in machine learning models, where the lack of representation for diverse populations can introduce inequalities in contexts such as hiring[24] or even danger for applications such as autonomous driving[25].

Data visualization. Mobility data is intrinsically spatio-temporal, describing the movement of individuals over space and time through multidimensional information. Visualizing the numerous dimensions of such data without compromising clarity or overwhelming the user's field of view, and offering freedom of exploration with natural gestures is an ongoing challenge. The conception of visualization techniques for spatial-temporal data must consider the natural properties of the data, e.g., the geographical position of locations and ordering of time units, while conveying the underlying dynamicity.

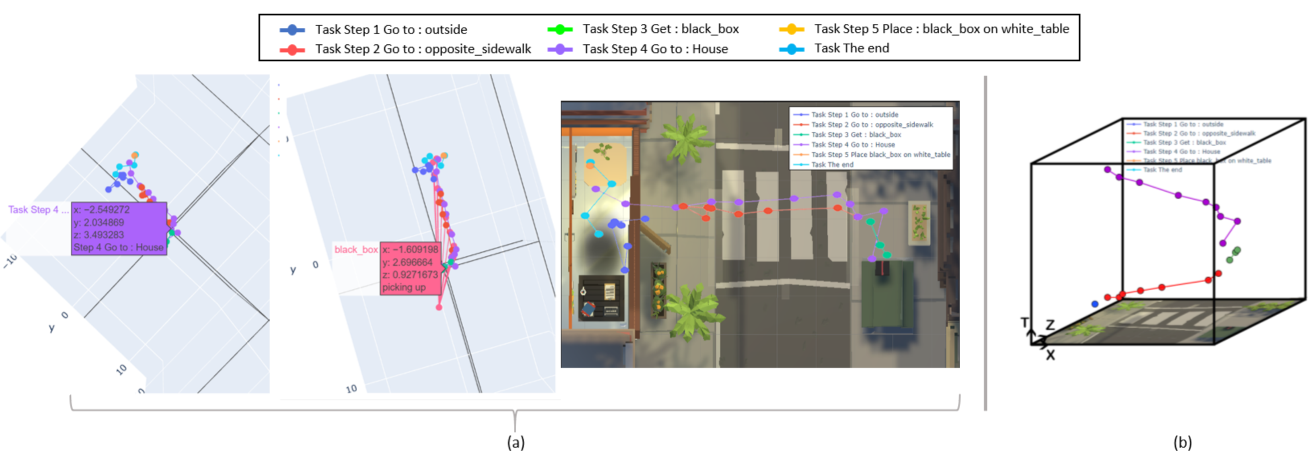


Figure 7. Example visualizations of user trajectory in condition 1 scene 1. (a-Left) Base visualization and detailed information upon hovering over a data point. (b-Right) Visualization using a space-time cube[26,27] that can potentially be implemented for immersive data exploration.

In the data presented in this paper, the spatial dimension is described on 3 axes, namely x and y describing the individual's horizontal position, and z the user's head position. We can make a base visualization with the scene (Figure 7(a)) using the *ex_visualization.ipynb* script, which offers reproducibility but retains simplicity with limited interaction (such as hovering) and no representation of time. Six different steps of the scenario are shown with different colors, and the dots correspond to the position of the head. However, this simplicity can make it difficult to assess perspective, as pointed out by Poirel et al.[28], affecting data analysis. Consequently, we took the decision to switch to immersive visualization with the temporal aspect, as suggested by Cliquet et al.[29] as such environments enhance depth perspective.

To tackle this issue, we propose the exploration of visualizations based on the space-time cube (STC)[26,27]: a three-dimensional representation, taking the form of a cube. It features two-dimensional space on its base, while the height dimension represents time. It depicts trajectories through line segments connecting spatial and temporal coordinates or data points while supporting the representation of thematic information, such as an individual's demographics, emotional state, etc. An example of this is shown in Figure 7(b). This makes the STC a powerful tool for communicating the underlying knowledge within the data through the representation of complex multidimensional data in a comprehensible and engaging manner.

Living contextual dataset. This work makes a strong attempt at creating a fully reproducible study, including the study design, system, data collection protocols, and data processing. We would like to thus introduce this concept of a "living contextual dataset" – datasets where living behavior in context is collected, processed, and analyzed with an aim to be fully reproducible such that future studies using the same protocol can compare to existing results with sufficient confidence. Moreover, the openness of the protocol to different modalities of data that can be correctly synchronized allows a fine-grained analysis of individual nuances of user behavior across datasets or study designs.

One such example usage is to enrich the existing datasets of pedestrian trajectory prediction for autonomous driving systems with different walking behaviors such as those impacted by low-vision conditions. We can envision an extension to this dataset with again other populations such as investigating the impact of aging. This will allow these models – which have direct consequences to security when deployed – to be refined with data that may be outside of the normal distribution, thus bringing advantages such as diversity and accessibility to AI methods.

Code availability

The pre-processed and synchronized dataset, along with some tools and usage examples, is available on Zenodo: https://zenodo.org/records/10406560. The GUsT-3D framework with which the study was conceived and carried out is registered under an open CeCILL license and can be requested here: https://project.inria.fr/creattive3d/gust-3d/.

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Author contributions statement

HW coordinated, participated in all aspects of the work, and wrote the manuscript. SR and AG are primary contributors on the study design and validation, cognitive science analysis, ethics review, and low vision. FR, MW, and LS engineered and developed the GUsT-3D framework and conceived the study. FR conducted the study with the assistance of KP, JD, CQ, and FG. FG and FR worked on the data synchronization. KP, SR, and AG validated the gaze and physiology data. KP and SR provided the statistical modeling usage note. FG and LS validated the motion capture data and provided the machine learning usage note. MH provided the survey description, analysis, and validation. CQ, AM, and MW provided the data visualization usage note. PK provided expert feedback on the study design and analysis throughout the project. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.

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Appendix: Full surveys

Table 5. We designed surveys for pre-experience, post-experience, and post-condition (following each condition). The participants were allowed to skip questions if they did not wish to respond. The UTAUT2 questionnaire is detailed in Table 6.

Questionnaire	Questions	Response options
	Pre-experience (T1)	
Study Information	User ID	Number
	Study Language	English / French
Demographics	Gender	Female / Male / Neither / I prefer not to say
	Age group	20-24/.../60+/ prefer not to say
Previous experience with VR and video games	Have you ever used a virtual reality headset?	Never / Rarely / Sometimes / Frequently / Always
	Have you every played 3D video games?	
Motion sickness	Do you experience motion sickness? (e.g., playing video games, transportation)	
	What situations cause motion sickness?	Open question
Technology acceptability (UTAUT2)	See Table 6	
	Post-condition survey	
Condition information	Setup	RW / SW ; NV / LV
NASA Task Load Index	- To what extent was the task mentally demanding? - To what extent was the task physically demanding? - To what extent was the task hurried or rushed? - To what extent did you succeed in carrying out the task requested of you? - To what extent did you have to be invested to attain your level of performance? - To what extent were you anxious, discourage, irritated, stressed, or annoyed?	10-point scale from (1) strongly disagree to (10) to strongly agree
Emotion	How do you consider the emotions experienced?	5-point scale from (1) calming, (3) neutral, to (5) intense
	How do you evaluate the positivity of the emotions experienced?	5-point scale from (1) negative, (3) neutral, to (5) positive
SSQ	- I felt ocular (visual) fatigue - I felt physical fatigue in the shoulders, back, and/or limbs - I have a headache - I had difficulties concentrating - I felt nauseated - I felt general discomfort	5-point scale from (1) strongly disagree to (5) strongly agree
Perception of the experience	- I found the task interesting - I found the task repetitive - The motion capture equipment interfered with the tasks - The physiology sensors interfered with the tasks - The 3D scenes were realistic - I felt that I was really walking in the 3D environment - I felt that I was really interacting with objects	
Difficulties during the task	Did you encounter any difficulties understanding the task or carrying them out?	Open question
Feedback	Do you have any other feedback on this conditions	
	Post-experience (T2)	
Presence questionnaire	Please evaluate your feeling of being present in the virtual environment	7-point scale from (1) not at all present to (7) as if it were a real place
	During the duration of this experience, did you often think you were really in the virtual environment?	7-point scale from (1) never to (7) all the time
	During the experience, which feeling was more dominant: being in the virtual environment of the the experience, or being elsewhere?	7-point scale from (1) being elsewhere to (7) in virtual space
	Concerning your memory of being in the virtual space: to what extent is the structure of the memory similar to that of places you have been physically today?	7-point scale from (1) not at all to (7) exactly like a real memory
Emotional state	Interested, Anxious, Excited, Annoyed, Irritated, Enthusiastic, Alerted, Inspired, Attentive	4-point scale from (1) not at all to (4) very much
Technology Acceptability (UTAUT2)	See Table 6	
Feedback	Do you have any other feedback or suggestions?	Open question

Table 6. The UTAUT2 technology acceptance questionnaire used in T1 and T2. Each question is responded on a 7-point scale from (1) strongly disagree to (2) strongly agree.

Subscale	Questions
Performance expectancy	- I find VR useful in my daily life - Using VR helps me accomplish things more quickly - Using VR increases my productivity
Effort expectancy	- Learning how to use VR is easy for me - My interaction with VR is clear and understandable - I find VR easy to use - It is easy for me to become skillful at using VR
Social influence	- People who are important to me think that I should use VR - People who influence my behavior think that I should use VR - People whose opinions I value prefer that I use VR
Facilitating conditions	- I have the resources necessary to use VR - I have the knowledge necessary to use VR VR is compatible with other tchnologies I use
Hedonic motivation	- Using VR is fun - Using VR is enjoyable - Using VR is entertaining
Price value	- VR is reasonably priced - VR is a good value for money - At the current price, VR provides good value
Habit	- The use of VR has become a habit for me - I am addicted to suing VR - I must use VR
Behavioral intention	- I intend to continue using VR in the future - I will always try to use VR in my daily life - I plan to continue to use VR frequently