RCQoEA-360VR: Real-time Continuous QoE Scores for HMD-based 360° VR Dataset

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Abstract

As immersive 360° video experiences through head-mounted displays (HMDs) gain widespread adoption, the need for real-time, fine-grained assessment of Quality of Experience (QoE) becomes increasingly critical for optimising user engagement and system performance. This paper introduces RCQoEA-360VR, a novel multi-modal dataset designed for continuous QoE evaluation in virtual reality (VR) environments. In a controlled study (N=32), participants watched five selected 360° video sequences across eight different video quality configurations (from the VQEG database) using a Vive Pro Eye while providing continuous QoE annotations via a touchpad-based input method, enhanced by the DotMorph peripheral visualisation technique. The dataset also includes synchronised physiological signals (electrocardiogram and galvanic skin response), behavioural data (eye and head movements) and post-viewing QoE ratings gathered through a within-VR interface. RCQoEA-360VR addresses a critical gap in existing public datasets by providing a fine-grained, synchronised multimodal data for immersive QoE analysis. It offers a unique and valuable resource for the research community, supporting a wide range of research applications, including QoE prediction, behavioural modelling, adaptive streaming, and implicit perceptual analysis.

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CCS CONCEPTS

• Human-centered computing • Human computer interaction (HCI) • HCI design and evaluation methods • User studies

KEYWORDS

360° video, Continuous QoE annotation, Eye and head movement, Multimodal QoE dataset, Physiological signals, Quality of experience, Virtual reality

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1 Introduction

Immersive 360° videos, delivered via Head-Mounted Displays (HMDs), are gaining widespread adoption across entertainment, education, and training applications [7]. Thes omnidirectional videos allows users to navigate virtual scenes through 3-Degree of Freedom (DoF) head movements (pitch, yaw, roll) offering users an enhanced sense of presence compared to traditional media [14]. However, users typically view only 15–40% of the spherical content at any moment, leading to highly dynamic and individualized attention patterns [3,16]. This viewport-dependent consumption creates significant opportunities for bandwidth optimization but demands new approaches to quality evaluation that account for spatial and temporal variations in perception [3,10,16]. Studies highlights how user navigation patterns, scene saliency, and motion dynamics significantly influence perceived quality and streaming efficiency in VR environments [1,2,6].

Assessing the Quality of Experience (QoE) in such dynamic and interactive scenarios remains a significant challenge. Current evaluation methodologies (absolute category rating) rely on post-stimulus ratings of overall experience [8]. While these methods work for traditional video content, they fail to account for the spatiotemporal variations in quality that can occur in 360° videos [20]. This limitation is particularly critical with adaptive tiling, where perceived quality can differ substantially across regions and over time depending on user interaction and viewport direction [3,20]. Furthermore, as the field moves toward 6-DoF VR and social immersive environments, where users can physically move within the space, expectations around immersion, realism, and responsiveness grow [17,18]. This demands user-centric research not just for improving technical performance, but also for understanding and predicting user behavior in real time. User-centric methods leveraging behavioral insights are now critical to optimizing QoE [16].

Moreover, existing datasets and evaluation methods often lack the granularity and multimodal data necessary for in-depth analysis of user experience. The landscape of 360° video datasets has expanded significantly in recent years, offering diverse resources for research in immersive media. Many existing datasets focus on specific aspects such as head movement (HM), eye movement (EM), or on discrete quality ratings like Mean Opinion Scores (MOS). For instance, datasets like Corbillon [3], PVS-HM [22], and Salient360 [4] provide behavioral data but lack subjective ratings entirely. Others such as VQA-OV [13] and ACR360 [5] include MOS but may not offer continuous annotations or extensive physiological data. More recent datasets, including Li et. al [12], RCEA-360VR [25] and CEAP-360VR [23] have introduced continuous emotion annotation synchronized with physiological and behavioral data, offering richer insight into user experience. Table 1 provides the comparison of existing 360° video datasets. However, these datasets are primarily focused on emotional response, not on QoE during immersive 360° video viewing, which is a critical metric for system performance, streaming adaptation, and user engagement.

Table 1. Comparison of Existing 360° Video Datasets

Dataset	Subj.	360 videos	Data modalities	Subjective ratings
Corbillon [1]	59	5	HM	No
PVS-HM [16]	58	76	HM	No
Salient360 [2]	57	19	HM,EM, saliency maps	No
VQA-OV [10]	221	60	HM, EM	MOS
Xu et al [17]	31	208	HM, EM	No
Li et al. [9]	93	73	HM	Emotion
RCEA-360VR [25]	32	8	HM, EM, peripheral visualization	Continuous emotion
CEAP-360VR [18]	32	8	HM, EM, PD, physiological (EDA, IBI, HR, SKT, BVP)	Continuous emotion
ACR360 [3]	60	4	HM, EM, GSR	MOS

The RCQoEA-360VR dataset addresses these limitations by offering a rich, synchronized collection of continuous QoE annotations, physiological signals including electrocardiogram and galvanic skin response, and behavioral data (HM and EM). In a controlled study involving 32 participants using a Vive Pro Eye HMD, participants viewed five 360° video sequences with eight different quality configurations from the VQEG database [8]. Unlike existing datasets, continuous QoE scores were collected via a touchpad-based input method enhanced by the DotMorph peripheral visualization technique, which offers real-time analysis of user experience dynamics. Post-video ratings collected within the VR environment further supplement the continuous annotations, offering a holistic view of user experience. This dataset builds upon prior work in real-time QoE measurement, particularly research investigating input modalities for continuous user annotation in immersive contexts [24,25], and serves as a valuable resource for advancing research in adaptive streaming, behavioral modeling, and QoE assessment in immersive media analysis.

2 Experimental Methodology for Dataset Creation

This section outlines the experimental protocol conducted with approval from the Technological University of the Shannon, Athlone campus Ethics Committee. It provides a detailed overview of the setup for data collection, including the sensors used to capture physiological and behavioural data and the VR stimuli presented to participants. It also outlines the procedures followed during the experiment, covering continuous and post-video QoE score reporting. Additionally, the section details the subjective evaluation methods, such as questionnaires, and the collection of qualitative feedback on participants' overall experience.

2.1 Experimental Setup

The experiment architecture is shown in Figure 1, and each part is described in detail below:

1. Participants view the immersive VR clips through the HTC Vive Pro Eye 1 HMD, as shown in Figure 2 (a) which has a resolution of 2,880 × 1,600 pixels, a 110° field of view and a refresh rate of 90 Hz. The audio signal is also sent to the HMD. During the experiment, participants sat on a swivel chair and were free to look in any direction. Correspondingly, head rotation and eye gaze data from the headset were recorded at 120 Hz.
2. A custom scene was constructed in the Unity Engine by the CWI team [26] to display 360° videos at 30 fps. It also shows

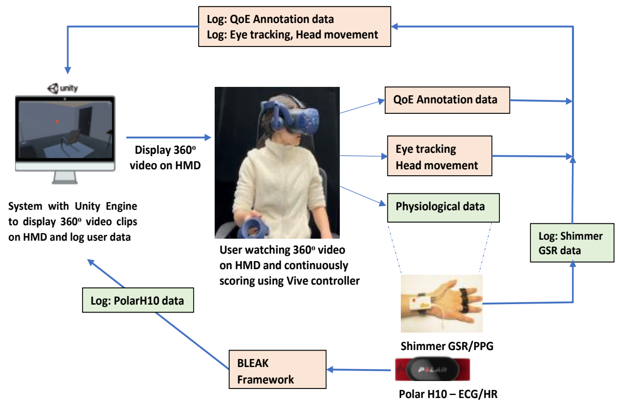

Figure 1. The RCQoEA-360VR experimental setup and the data flow between different sensors and components.

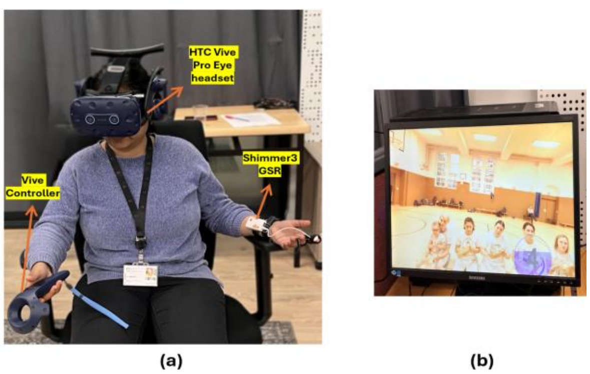

Figure 2. A participant engaging with a 360° VR experience using an HTC Vive Pro Eye headset, Vive controller and a Shimmer GSR unit on the left wrist in (a) and 360° video display with a continuous rating feature in (b).

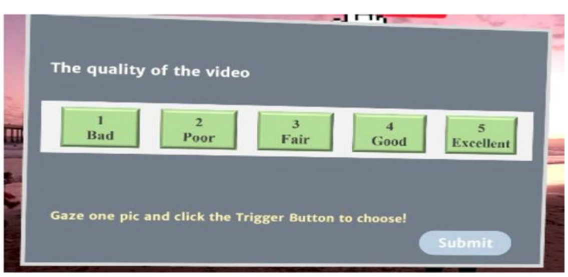

Figure 3. Within-VR post-QoE question asked of the participants at the end of each video to provide a 5-scale MOS rating.

the annotated feedback based on users' continuous ratings (see Figure 2 (b)). The project ran on a 2.20 GHz Intel i7 computer with an Nvidia RTX 2070 graphics card.

3. Participants used the Vive controller to provide continuous QoE ratings by moving the touchpad up or down during video playback. After each video, they gave a post-video MOS rating using a within-VR rating panel (see Figure 3).
4. Participants' physiological signals were captured through the Polar H10 chest band, which measures ECG data. GSR data was recorded using a Shimmer GSR wristband worn on the non-dominant hand. PPG data was also collected using the Shimmer GSR device that connected the sensor to the finger. A built-in application calculated HR from PPG.
5. The BLEAK framework, with LSL and LabRecorder [27], streamed ECG data from the PolarH10 to the desktop. GSR data was recorded through the Shimmer Consensys desktop app and stored on an SD card. All devices were synchronised with the laptop's clock.
6. After each block, participants completed the simulator sickness questionnaire (SSQ) [11], Igroup presence questionnaire (IPQ) [21] and NASA Task Load Index (NASA-TLX) [9] forms. A semi-structured interview followed at the end.

2.2 Implicit Measures

In this dataset, physiological (ECG, GSR, and PPG) and behavioural data (eye movement and head movement) were continuously captured while participants watched 360° VR videos. The Polar H10 chest belt, Shimmer3 GSR unit and HTC Vive Pro Eye are discussed in the next sections.

2.2.1 Polar H10. The Polar H10 is a heart rate monitoring device utilising bluetooth low energy (BLE) technology to transmit data to other devices. The Polar H10 employs a single-lead ECG integrated into an elastic-polymer strap, ensuring a comfortable and secure fit during use. The chest belt can be used as a means for continuous monitoring of ECG, evaluation of rhythm and screening of atrial fibrillation in patients with a wide range of heart diseases [19].

The BLEAK framework was employed to establish communication between the Polar H10 and desktop applications. BLEAK serves as a versatile BLE framework, compatible with both smartphones and desktop environments. Its cross-platform capability allows smooth operation across different operating systems, enhancing accessibility and usability [15]. Following the steps outlined at the link[1], a desktop connection to the Polar H10 using BLEAK was established (see Figure 4). The integration with the lab streaming layer (LSL) further enhances the Polar H10's functionality. LSL is designed for unified time series data collection in research experiments, handling networking, time synchronization, real-time access and centralized data collection. ECG data captured by the Polar H10 at 130 Hz was streamed over

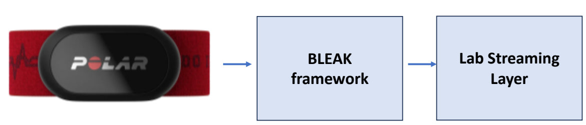

Figure 4. ECG data acquisition pipeline using PolarH10 chest belt and BLEAK framework

[1] https://github.com/markspan/PolarBand2lsl?tab=readme-ov-file

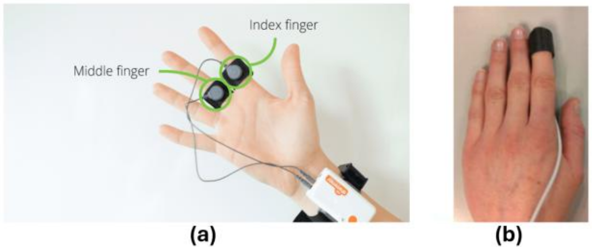

Figure 5. Data acquisition setup using Shimmer GSR unit for capturing (a) GSR and (b) PPG signals.

a local network to a desktop computer. The streamed data was recorded using LabRecorder, a component of the LSL accessible at the link[2], facilitating the loading and analysis of recorded data.

2.2.2 Shimmer GSR. GSR, also known as EDA, measures the electrical conductance of the skin. The GSR signal was captured using the Shimmer3 GSR unit, which was extended with a GSR module board (130 Hz). In this experiment, two electrodes were placed on the index and ring fingers of the non-dominant hand to monitor skin conductance, as shown in Figure 5 (a).

The Shimmer GSR+ Unit extends its capability with an Optical Pulse Sensing Probe that provides a PPG signal from a finger, ear lobe or other capillary tissue location on the body. This signal can be used to estimate pulse or heart rate. In this experiment, a finger electrode was used to record the PPG signal, as shown in Figure 5 (b).

The Shimmer software application, ConsensysPRO, was utilised to configure the GSR sensors for logging data to the SD card. The software also allows the real-world timestamp from a PC on a Shimmer device. Additionally, the application performed PPG-to-HR conversion. The ConsensysPRO software was used to read the data from the SD card at the end of the study.

2.2.3 Behavioral data. The HTC Vive Pro Eye headset includes integrated eye-tracking technology that captures behavioural data including eye movement and head movement. The eye-tracking capabilities measure gaze direction, pupil dilation, and fixation duration at 120 Hz. Head movement tracking monitors rotations, orientations and positional movements continuously in terms of x, y and z rotations (yaw, pitch and roll) from the headset at 120Hz, providing data on how users physically explore 360° VR spaces.

To ensure accurate eye-tracking calibration was performed, while head movement tracking was automatically managed by built-in sensors and external SteamVR base stations. During the VR session, both eye and head movement data were continuously captured as part of the behavioural data collection. After the session, the collected data was exported.

2.3 Subjective Measures

The study employed a combination of subjective evaluation methods to assess QoE: (a) continuous self-reporting, (b) post-stimuli MOS scoring, (c) questionnaires, and (d) semi-structured interviews.

2.3.1 Continuous QoE self-reporting. Building on prior work [24] that developed touchpad (up/down) annotation input techniques with DotMorph visualisation for peripheral feedback, participants in this study report their QoE scores continuously while watching a 360° VR video displayed on their HMD. The ratings are in terms of MOSs on a discrete 5-point scale (1-Bad, 2-Poor, 3-Fair, 4-Good, and 5-Excellent). Scores are annotated using the touchpad, allowing participants to make up/down movements at a frequency of 10 Hz.

In the bottom-right viewport, a circle dot with a tick label visually indicates the annotation state, with the fill level changing based on the input. DotMorph employs a continuous vertical fill to represent the quality score, while an integer tick label is embedded in the centre to convey the current score (see Figure 6). Participants placed their dominant hand's thumb on the touchpad and dragged it up or down to report their QoE scores (see Figure 7).

2.3.2 Post-stimuli MOS Score. At the end of each video, participants were asked to rate the quality of the video using a 5-point scale for MOS, as illustrated in Figure 3.

2.3.3 Questionnaires. At the end of each block, participants were asked to complete the SSQ, IPQ and NASA-TLX questionnaires. The SSQ assesses symptoms of motion sickness in the virtual environment due to visual impact, including 16 indicators that describe different physiological sensations SSQ responses were collected from each participant before the experiment began and after every block.

Participants also completed the IPQ after every block, which consists of 14 items. To measure cognitive load, details from the

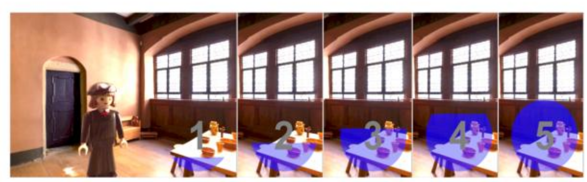

Figure 6. DotMorph visualization with a circle and an integer tick label fixed to the bottom-right corner of the viewport, which varies in fill (up/down) with annotation state.

Figure 7. Touchpad annotation technique (up/down).

[2] https://github.com/sccn/labstreaminglayer

NASA-TLX were collected from each participant following each block.

2.3.4 Semi-structured Interview. At the end of the experiment, a semi-structured interview was conducted with the participants. The interview included the open-ended questions to gather user feedback on video preferences, perceived differences in video quality, comfort during the rating process, suggestions for improvement, and alternative input methods.

2.4 Test Stimuli

Five different quality types of 360° video sequences of 30 seconds (including audio component) with uniform (using homogeneous QPs) and non-uniform (using different configurations of tiles) coding degradations from the VQEG database [8] were used as stimuli in the tests. The VQEG database contains MOS scores from ten laboratories and more than 300 participants. They were all in equirectangular projection, monoscopic and had a resolution of 30 fps. Screenshots of the selected video clips and their main characteristics are listed in Table 2.

For each of the five selected 360° video sequences, eight different video quality configurations from the VQEG database were selected as stimuli, including four uniform encodings (using homogeneous QPs) and four non-uniform encodings (using different configurations of tiles). For the uniform configurations, the following QPs were used: 15, 22, 32 and 42. For the non-uniform configurations (QP = 22 6x3 gradual, QP = 22 6x3 abrupt, QP = 22 8x5 gradual, QP = 22 8x5 abrupt), two different structures of tiles were used. Smooth and abrupt transitions between neighbouring tiles were considered, as illustrated in Figure 8 [8].

2.5 Experimental Procedure

The experimental procedure, as shown in Figure 9, includes an information and screening phase, a training session with eye tracker calibration and the main experiment, which lasted approximately 50 minutes. The experiment was conducted in a controlled air-conditioned room maintained at 20-25° Celsius.

Table 2. Properties of the selected test video clips

Video Name	Description	Resolution
VSenseLuther (VL)	Video with animation content and a main character. Contains various shots (indoors and outdoors) and audio	4,096 x 2,048 30fps
VSenseVaude (VV)	Video where a girl speaks to the camera. Contains audio and various indoor and outdoor shots	4,096 x 2,048 30fps
Oculus Motion (OM)	Camera moving in a city. Contains music and two shots: one in daylight and one at night.	3,840 x 2,160 30fps
NokiaFlamenco (NM)	Indoor dance course, with ambient audio. Contains stitching artifacts.	3,840 x 2,160 30fps
BrazilMusic (BM)	Indoor scene of a band playing Brazilian music. With audio.	4,096 x 2,048 30fps

#Tiles	Transition	ROI	QPs							
8x5**	Smooth	90°	42	37	32	22	22	32	37	42
6x3	Smooth	120°	42	32	22	22	32	42		
8x5**	Abrupt	180°	42	42	22	22	22	22	42	42
6x3	Abrupt	120°	37	37	22	22	37	37		

Figure 8. Settings for the non-uniform coding configurations

2.5.1 Information & Screening Phase. Before the experiment, the participants were asked to sign a consent form, fill out a background information sheet and complete a pre-SSQ questionnaire. They were then provided with a general explanation of the experiment, including within-VR rating and DotMorph. Participants were told that they would be wearing a headset to view the immersive videos and that they could request to stop participating at any time if they felt uncomfortable or had some form of simulator sickness. A Monoyer Chart was used to verify their normal or corrected-to-normal vision. The accepted colour perception was evaluated with the Ishihara Test.

2.5.2 Training Phase. During the training session, participants sat in a swivel chair and wore the equipment, including the HTC Vive Pro Eye headset, PolarH10 chest belt, Shimmer wristband and Vive controller, as illustrated in Figure 2 (a). They were given time to get comfortable with the VR environment. The participant's interpupillary distance was measured to adjust the headset lenses accordingly. Participants then calibrated the eye tracker by following instructions on the system dashboard to ensure accurate tracking.

The training commenced with participants focusing on a colour-changing cube, which turned red to signal them to concentrate, as shown in Figure 10. After two seconds, a video was played. While watching, participants learned to report the QoE score continuously using the right controller by making up-and-down movements on the touchpad. At the end of the video, they provided a post-QoE score through a within-VR panel, selecting their score by gazing at it and pressing the trigger button to submit. This process was repeated until participants felt comfortable and confident with the system. They watched both high-quality and low-quality training video clips of the

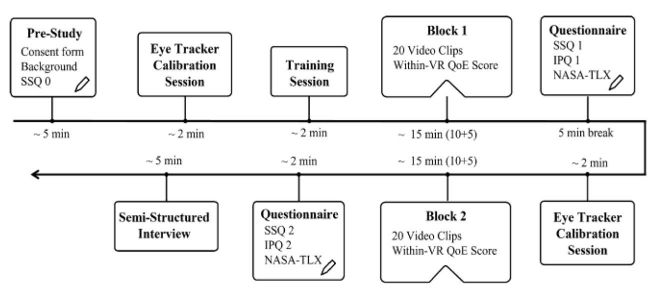

Figure 9. The RCQoE 360VR experiment procedure.

Figure 10. Participants focused on the Cube until it became red.

Oculusbeach video, as detailed in Table 3.

2.5.3 Testing Phase. To avoid discomfort caused by wearing HMD for an extended period, the experiment was divided into two blocks. Each block contained twenty 30-second videos and lasted around 14 minutes. The order of the blocks and the order of the videos in each block were counterbalanced using Latin Square Design. Prior to each video, the participant focused on the Cube until it became red; after 2 seconds, the video played.

During the video playback, QoE ratings were continuously collected from each participant, who annotated their scores using a touchpad at a frequency of 10 Hz. After each video, participants provided a rating for the video quality. Physiological signals, ECG, GSR and PPG, were collected from the PolarH10 chest belt and Shimmer3 GSR device during the study period. Following each block, participants completed the SSQ, IPQ and NASA-TLX forms. At the end of both blocks, participants participated in a semi-structured interview featuring five questions regarding their user experience.

2.5.4 Participants. Thirty-two volunteers, consisting of 22 males and 10 females with ages ranging from 18 to 47 (mean age of 33), took part in a data collection experiment. These volunteers were recruited from the Technological University of the Shannon, Athlone Campus, Ireland and represented different cultural backgrounds. All participants had a good command of English and were provided with information in the same language. They were asked about their use of corrective eyewear and prior experience with VR.

3 Supplementary Material

The presented RCQoEA-360VR dataset is publicly available on GitHub (https://github.com/sowmyyav/RCQoEA-360VR-Dataset), under the following license: Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) license. The dataset description and README files in the root folder explain the dataset contents. The repository consists of raw data from all 32 participants, the processed physiological data and other metadata along with the video stimuli, unity project scripts and data preprocessing scripts. The behavioral and physiological data with continuous and post-viewing QoE scores can be used for machine learning and deep learning experiments.

Table 3. Properties of the training video clip

Video Name	Description	Resolution
OculusBeach (OB)	Scene with music of a beach at sunset with people dancing and moving.	3,840 x 1,920 30fps

4 Conclusion

The RCQoEA-360VR dataset addresses these gaps by offering a multimodal dataset specifically designed for continuous QoE assessment during 360° video playback in HMDs. In conclusion, the RCQoEA-360VR dataset offers a multimodal resource for continuous Qoree assessment in 360° VR environments. By combining real-time subjective ratings with synchronized physiological (ECG, GSR) and behavioral (eye and head movement) data, it enables detailed analyses of user experience. This comprehensive, fine-grained dataset enables nuanced analysis and modeling of user experience, supports the development of predictive QoE algorithms, and advances research into adaptive streaming and perceptual inference in VR.

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