Squeeze and Slide: Real-time continuous self-reports with physiological arousal to evaluate emotional engagement in short films of contemporary dance

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Engagement is a broad and multifaceted research subject. Self-report engagement data of time-based experiences such as life performance or films is mostly collected through post-hoc questionnaires. The present study compares two devices that allow for real-time continuous self-report while watching 2 short films featuring contemporary dance. The first device is a squeeze ball with a pressure sensor inside and the second device a mechanical linear slider. Users are prompted to indicate their emotional engagement throughout each film using a device. Electrodermal activity (EDA) was also recorded as an indicator of arousal. Across a study involving 31 participants, the squeeze ball and slider reveal comparable overall correlations to EDA data. However there are indications of user-preference for the squeeze ball in the context of rating emotional involvement.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; **User studies**.

Additional Key Words and Phrases: real-time measures, engagement, film, dance, EDA, embodiment, neuroaesthetics

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1 INTRODUCTION

Experiences like performance or film are dynamic and unfold over time [30]. Neuroaesthetics of dance and Human-Computer Interaction (HCI) research aim to quantify our engagement with these experiences [13]. As a pivotal element in human interactions and focal point of research in various fields, engagement serves as a precursor to meaning-making, value creation, and connection [6]. Yet, engagement remains a complex and challenging concept to precisely define as it grapples with diverse terminology, measurement method ambiguity, and context dependency [4, 6, 11, 45].

Engagement is mostly assessed through autonomous physiological data, post-hoc self-report and, increasingly, real-time ratings [48]. Most real-time continuous self-reports involve visual feedback with linear scales, like screen-based interfaces or physical sliders. In measuring engagement in dance, a gap in the literature lies in the exploration of audience engagement through datasets that incorporate real-time continuous self-report, specifically measures that stay close to the physical body i.e. through proprioceptive feedback [10]. This raises questions around both how such data might best be collected, and how it can be interpreted [15].

The current study evaluates two continuous real-time self-report devices - a mechanical slider and a stress ball - by examining their correlation with physiological arousal while participants watch two short films involving dance.

2 RELATED WORK

Engagement may vary from immediate and momentary experiences, such as watching a film, to more prolonged interactions, like the frequency of theatre visits [23]. Rather than measuring engagement as a whole, methods may focus on either cognitive, affective, and behavioral components of engagement [49].

Recent research has shown promise in exploring real-time continuous self-report methods, both within and outside laboratory settings, particularly in contexts such as video analysis or live dance performances. Despite the potential, self-reports face common challenges: interruptions in real-time reporting or low response rates, as well as potential issues related to retrospective interpretations if conducted post hoc [11, 15].

An early work pioneering continuous self-report in video and life performance is by Stevens *et al.* (2009)[40]. They used a handheld feedback system with a technical drawing pad and a stylus and showed that arousal had a higher correlation to surface features of dance than valence. A similar measure used finger tracking in complement to physiological measures, demonstrating the relationship between engagement synchrony and enjoyment [46].

Sliders are another common measure to answer prompts during 4D stimuli. This refers to stimuli that include the dimension of time and feature dynamic content and or narrative such as videos, animations or performances. In a recent laboratory study, difficulty ratings of online lectures were continuously recorded with a physical slider from a MIDI controller [39]. They successfully identified points of difficulty in the lecture videos through the participants' ratings which were in accordance with the difficulty level predicted by the instructors. This study's slider was attached to a fairly large device which would be a complicated set up in an ecologically valid setting. Other works have also used either physical or digital sliders to measure engagement, valence, or pleasure and arousal[5, 19, 26, 38]. Laurans *et al.* point out the congruence between affect and movement as well as the notion of embodied emotion, like approach and avoidance, arguing in favour of using a linear slider to rate emotional valence or intensity [26].

The sliders referenced here are either fairly large, attached to a larger device, not wireless or screen-based. For the purpose of using sliders to rate live performances, the device needs to be relatively small, non-intrusive and wireless. Further it can be argued that emotional intensity can also be embodied through gripping and releasing (like holding onto the seat when the plane lands) as opposed to away-towards movements. A recent study examined approach avoidance behaviour through a grip-force device handled with the right thumb and index finger the rate positive or negative images [31]. The study found significant evidence for relationship between the visual stimulus and the movement response. Further, participants had shorter response times when the response prompt was affect congruent, i.e. approach-grip and avoid-let go of grip.

There have been studies examining whether giving continuous self-report alters the aesthetic experience [19, 48]. One study exposing participants to a 40 minute musical piece concluded that the task of real-time ratings did not alter the subjective experience [48].

Continuous real-time physiological activity provides implicit indices of excitement and arousal which are operators of engagement [34]. Accordingly engagement can be distilled and conceptualized through various lenses, such as emotion laden attention [38], valence and arousal [25], or positive excitation [1].

Arousal - physiological excitation- has been used as an index of attention and emotional engagement with 4D stimuli. It can be measured with EDA and they are linearly correlated [1, 24, 25].[1] Noteworthy advantages of EDA include cost-effectiveness, extensive research backing, and non-invasiveness, as well as relatively easy administration [1].

[1]Note: EDA is referred to as Galvanic Skin Response (GSR) in earlier literature, but the two terms are synonymous, so for consistency we adopt EDA.

Drawbacks include proneness to noise and artefacts such as room temperature and physical fitness. Nevertheless, they provide crucial interpretive context for self-report data and vice-versa [42].

Several studies have implemented a mixed methods design, complementing EDA with subjective measures. For example a study by Latulipe *et al.* had 9 participants watch an 11-minute dance performance while wearing an EDA sensor and giving continuous deliberate engagement feedback with a slider [25]. They chose arousal as the most relevant component of engagement in dance-/theatre performance. They used different prompts for the slider use instructions, namely, 'No Engagement to High Engagement', 'Love it! to Hate it!' and 'No Emotional Reaction to Strong Emotional Reaction.' Some of their participants reported difficulty in detaching valence form the work meaning they would only indicate engagement when they liked what they saw.

The present study is concerned with momentary engagement, specifically arousal and emotional involvement, whilst watching a dance work made for screen. We implemented two real-time measures - subjective self-report and objective physiological arousal - to explore how they correlate. We investigate two wireless handheld self-report devices: a small physical slider and a BlueBall (BB) sensor, which is a squeeze ball with a pressure sensor inside. We introduce the BB sensor here as a novel and rudimentary way of gathering proprioceptive feedback. Both devices were chosen as they can be operated using one hand and do not provide a visual distraction.

3 EXPERIMENT

Our experiment is framed within engagement in a 4D stimuli, but we use this to compare two data collection methods. In a 2 x 2 between-subjects design (factor1: short film; factor2: device) participants watched 2 short (10 minute) dance films and used either a slider or a BB to give continuous self-report of their involvement in counterbalanced order. Throughout each film we also collected their EDA (within-subject). We pose the following questions:

(1) What is the difference in User-friendliness of each self report device?
(2) How does each device relate to physiological arousal?

3.1 Participants

31 participants (10 male, 13 female, 8 diverse) aged 21-46 (*Mean* = 28.6, *SD* = 5.8) were recruited from Goldsmiths University of London in January 2024. All participants were compensated with a £5 voucher after completing the study. 15 participants were students in a field related to art. 16 participants were not students of which 10 worked in a field related to art. The participant number was gathered with regards to the CHI local standards of sample size at CHI and previous literature [7, 41]. All participants gave consent for use of their anonymized data. The study was approved by the ethics board of the senior author's institution.

3.2 Materials

3.2.1 Short Films. We selected our video material based on the criterion that it should be a complete dance work made for camera (as opposed to a live performance that was recorded, or shorter snippets of a longer piece) with an emotional narrative. This was judged at face value by the authors. As we were not aware of affective standardization methods in film, we chose stimuli similar in duration and type [41]. We selected 2 contemporary dance films, which we refer to as "Iris" and "Endurance", each approximately 10 minutes long. This duration was chosen in accordance with previous studies on engagement with dance and or film [25, 40, 41]. The films are freely available on YouTube under:

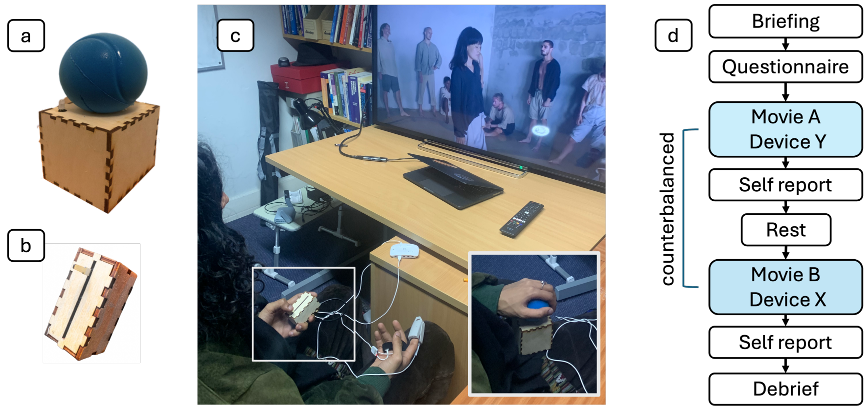

Fig. 1. (a) BB and (b) slider devices, (c) experimental setup, with insets showing slider and BB, and (d) procedure

https://youtu.be/vvNwIZj0bG4 and https://youtu.be/1fBMzKlMCxQ. "Endurance" was created by Imre Van Opstal and performed by Batsheva Dance Company. "Behind the Blind Iris" was created by Botis Seva and Douglas Bernardt.

3.2.2 Slider. The first device we built to collect real-time self reports of arousal is a mechanical linear slider (B103 10K Ohm Slide Potentiometer), 6 cm long, in the style of a fader akin to dj-mixers. It is not spring-loaded, hence, remains in place when untouched. [39]. See Figure 1 (b). This is connected to a Raspberry Pi Pico W, which samples the slider position at 10Hz and sends the readings wirelessly via User Datagram Protocol (UDP) to a laptop. The plywood casing measures approximately 7cm long and 3.5 cm high and wide. Participants were asked to hold the slider in their dominant hand and manipulate it with their thumb according to their arousal.

3.2.3 BlueBall. The BB sensor is a foam stress ball with a pressure sensor (RP-S40-ST High Accuracy Thin Film Pressure Sensor) inside. See Figure 1 (a) The ball has an easy-to-grasp surface and a diameter of roughly 7 cm. The ball is attached to a plywood box, approximately 7x7x7 cm containing a micro controller and a battery. Readings are sampled at 10Hz by a PicoW and sent over WiFi to a laptop. Participants were asked to hold the device in their dominant hand and continuously squeeze the ball in accordance to their arousal throughout each film. Note that neither slider nor BB require the user to look at the devices when in use. Both devices are lightweight and can easily be held in one hand, or rested on a knee, for long periods of time.

3.2.4 Electrodermal Activity and Heart Rate. As a continuous measure of physical arousal, participants wore EDA and HR sensors on their non-dominant hand to avoid motion artifacts [15]. A biosignalsPlux device was used to capture EDA (using dry electrodes on the middle and ring finger) and HR (using a blood volume pulse sensor on the index finger) at 20 Hz and send these via TCP/IP to a laptop [2]. See Figure 1 (c). Data was continuously collected throughout, including a 3 minute rest period as a baseline. Note: here we consider only EDA and leave HR analysis for future work.

3.2.5 User-friendliness questionnaire. The questions to rate each self-report device are taken from Stevens and colleagues [40]. It is a 6 item inventory on a 5-point Likert scale (totally disagree - totally agree). The questions ask about the enjoyment, ease, and clarity of using the device.

[2] biosignalsplux, PLUX wireless biosignals S.A. (Lisbon, Portugal)

3.2.6 Subscale Goldsmiths Dance Sophistication Index (GDSI). The GDSI is a self-report inventory of dance experience using a 7-point Likert scale (Completely Disagree - Completely Agree) [36]. The present paper uses a separate 6 item subscale of the GDSI assessing observational dance experience which includes liking to watch people dance and frequency, choosing dance performances over theatre plays, having knowledge about dance and choreography and being prepared to travel for dance workshops or performances. All questionnaires were conducted through the survey platform Qualtrics XM, which participants completed on their mobile phones.

3.3 Data pre-processing

All data were pre-processed in Python3. The self-report devices (BB and slider) were time-locked to the onset of each film (playback button) and saved together with the timestamps of the local laptop clock. The physiological data were synchronised and saved using the same clock.

The self-report data are first low-pass filtered (3rd order Butterworth, cutoff 5Hz), before being smoothed using a 60s rolling mean window. EDA tonic and phasic features are extracted from the raw signal using the pyEDA toolkit [3], and the data is downsampled to 10Hz to match the self-report data. All data are z-scored to ensure comparable ranges. [3]

3.4 Procedure

Figure 1(d) outlines our procedure. Upon arrival, participants were asked scan a QR code to a Qualtrics survey. They read a description of the experimental procedure in plain language and signed an informed consent. A short demographics questionnaire asked about their age, preferred pronouns, gender (if applicable) and if their studies or field of profession were related to arts. They were seated in front of a flat screen monitor. The experimenter verbally presented the sensors and explained how to handle them. During a training phase participants tried out the self-report devices and got visual feedback from the serial monitor. To check that they had control over each device, the experimenter asked them to squeeze or slide a specific value. Then the experimenter set up the EDA sensor on their non-dominant hand and asked the participants to hold their hand as still as possible. The self-report device was held in the other hand and participants were reminded to move the slider (low-high) or squeeze (harder for higher involvement) the BB in relation to their emotional involvement.

During the film the experimenter waited outside and came back as soon as it ended. Participants rated the device usability on Qualtrics and indicated one moment they remembered from the film. After a short break they repeated this procedure with the second film and device. Upon completion they were debriefed and thanked for their participation with a £5 compensation.

4 RESULTS

4.1 User-friendliness ratings

3 of the Qualtrics questionnaires were still in progress at the time of the analysis, leaving 28 participants. As both films portray dance we tested the participants' experience in observing dance with the GDSI on a 7-point Likert scale (Completely Disagree - Completely Agree). The average GDSI score was 3.55 (SD = 0.51) indicating a nearly perfect midpoint of the scale suggestive of a moderate level in experience of watching dance.

[3]The dataset and analysis scripts can be downloaded from OSF: https://osf.io/65hk8/

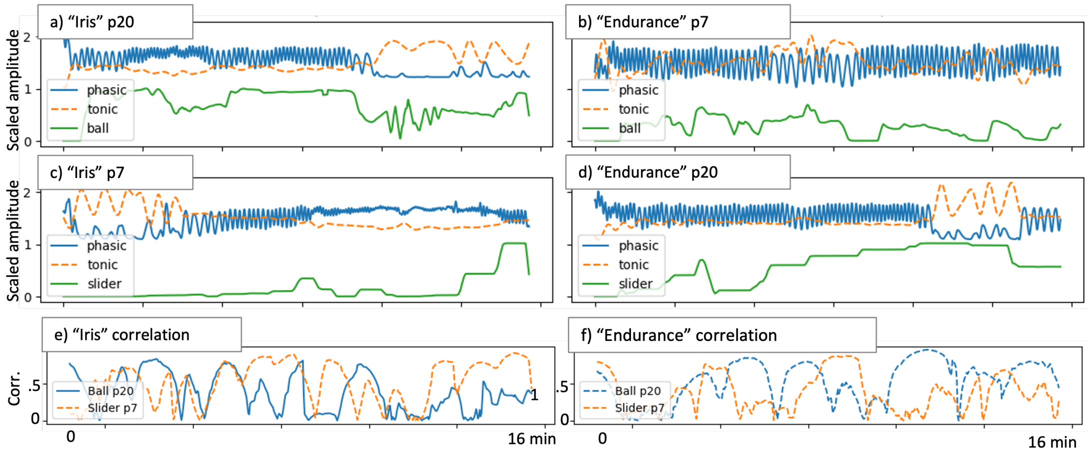

Fig. 2. (a-d) Example signals from 2 participants (p20 and p7) showing EDA phasic and EDA tonic signals alongside either ball or slider response, during 16 minutes of either film (Iris/Endurance). Signals are scaled and y-shifted for plotting. (e-f) sliding window correlations of ball/slider with EDA tonic.

Question	BB	Slider
I enjoyed using this device	3.63 (SD = 1.21)	2.86 (SD = 1.34)
I found this device easy to use	3.81 (SD = 1.3)	3.43 (SD = 1.5)
I found using this device distracted me from the performance	1.89 (SD = 1.45)	2.93 (SD = 1.54)
It was easy to rate my "emotional involvement" continuously using this device	3.04 (SD = 1.32)	2.71 (SD = 1.3)
I would prefer to use pen and paper to rate engagement after the performance than use this device to rate engagement continuously during the performance	1.16 (SD = 1.55)	2.08 (SD = 1.93)
The instructions about using the device were clear.	4.82 (SD = 0.39)	4.65 (SD = 1)

Table 1. Results of the usability ratings from N=28 participants, from 1 (Totally Disagree) to 5 (Totally Agree)

The mean user-friendliness scores of the 2 devices using a 5-point scale are shown in Table 1. In general, ratings for both devices deviate from the midpoint of 2.5 (Totally Disagree - Totally Agree), except ease of rating emotional involvement with the slider (Mean = 2.71, SD = 1.3).

Distraction and ease of use is regarded as assessing cognitive load of using the devices [40]. While ease of use ratings were comparable for both devices, participants found the slider to be more distracting (Mean = 2.93, SD = 1.54) compared to the BB (Mean = 1.89, SD = 1.45) by a statistically significant distinction ($t(25) = -2.33$, $p = 0.028$). Further support for the BB's preference emerged from a paired-samples t-test for enjoyment of device use ($t(26) = 2.39$, $p = 0.024$) and a preference over pen and paper ($t(22) = -3.01$, $p = 0.006$). These findings collectively suggest a slight preference for the BB. Lastly, clarity of instruction received the highest ratings overall, not differing significantly (BB: Mean = 4.82, SD = 0.39; Slider: Mean = 4.65, SD= 1).

4.2 Time-series analysis

Figure 2 shows 2 participants' real-time data plotted over the duration of each short-film (Iris and Endurance). Subplots a-d show that the BB signal is more nuanced than the slider's which is more step-wise. Comparing phasic and tonic EDA across participants (a and c, or b and d) suggests that the 2 individuals each had a different experience watching the same movie. The subplots further show that the tonic and the self-report lines have moments of similar behavior, especially in the rate of change, regardless of intensity. (Note that plots for all participants can be found alongside the full dataset at https://osf.io/65hk8/.)

The slow-moving tonic signal of the EDA appears to have a stronger similarity to the self-report data. We therefore chose window (with 10 second jumps) across 24 participants. The overall mean moving window correlation for the BB was 0.32 (SD = 0.20) and for the sliders 0.35 (SD = 0.22). Figure 2(e-f) show examples for both correlations for Iris and Endurance, respectively. For Iris (subplot e), BB and Slider follow a similar pattern of correlation fluctuations throughout. For Endurance this pattern is slightly offset.

To investigate if the correlations are stronger for either device or stimulus, we conducted a 2x2 ANOVA with film (Iris and Endurance) and device (BB and slider) as factors, no interaction term. We excluded 7 participants due to missing or corrupted data (5 due to poorly connected EDA electrodes, 2 due to network issues), resulting in N=24. Neither the factor device ($F(1,45)=0.75, p=0.391$) nor the factor movie ($F(1,45)=0.02, p=0.876$) was significant. Hence, with this analysis there is no clear indication if either self-report device correlated better with the EDA.

5 DISCUSSION

The plots in Figure 2 suggest that there are moments of simultaneous peaks and changes in deliberate and autonomous data. Occasional small offsets in these moments suggest potential response latency in the self-report signal or EDA [2, 44]. Further smoothing can address this but with a trade-off in resolution [42]. Generally, reactions in dynamic art forms are probably delayed by a few seconds and people typically have different timings [16, 43].

Low correlations might arise because sustained periods of signal dissimilarity dilute instances of heightened signal synchrony. Hence, correlating the whole time span is sub-optimal here. However, the necessity to analyse connections across the whole time span remains, but we may need new or different ways to do so. A study on audience responses to live dance performance by Han *et al.* used detailed plots with multiple similarity measures, to reveal close links between overall audience physiology and the planned choreography [18]. In future work we plan to deepen our analysis using a group of professional dancers and choreographers who will externally assess the stimuli. We will then align these ratings with periods of elevated arousal. Informing and sectioning our data could also enhance its suitability for more complex time-series analysis, such as dynamic time warping [9, 12].

5.1 Kinesthetic Feedback and Applications in Live Performance

Engagement is not only in our minds but emerges from our kinesthetic experience and empathy as well as sensory feedback [20, 32, 35, 37, 50]. An advantage of the BB compared to the slider is that it facilitates an embodied response by the user expressing or releasing tension. The congruence between movement and affect suggests that engagement, particularly emotional involvement, can be effectively captured through embodied cognition [21, 27]. However, it begs the question if there is an effect of interacting with the self-report device itself. For example, if the haptic feedback of the sensor heightens bodily awareness, this may influence the aesthetic experience [14, 22].

One novelty of the BB input method is that it reduces the need for participants to switch modality i.e. from watching dance to indicating a response through the body. The BB remains closer to the sphere of rudimentary bodily movement, rendering a closer translation of the experience into a rating than the slider which can be more cognitively demanding. That said, the linear interaction with a slider may be easier for those people who experience little bodily awareness during their daily life. Future work might explore this relationship between input modality and levels of body awareness.

Engagement is studied across diverse contexts like computer interactions, art, conversations, daily work, and classrooms [2, 28]. This raises intriguing questions about the impact of physical and social liveness on the experience, reflected in the data [1, 18, 33]. Both devices offer significant potential to enhance such real-time, ecologically valid studies. The prompt is flexible and can capture other continuous 2-dimensional responses like presence, tension, aesthetic pleasantness, excitement and so forth. As such, these devices hold applicability in clinical, educational psychology, HCI and various interactive environments, offering insights into the dynamics of engagement. Understanding the relationship between continuous explicit and implicit engagement remains a crucial task for further research [42].

5.2 Limitations

Both devices raise several considerations. Firstly, the use of either device may alter the actual experience [29]. The concept of emotional involvement may be ambiguous for the participants. The cognitive load imposed by the task of continuously reflecting on this, may alter the actual experience. The impact of such devices on cognitive load has been contested by previous studies (e.g., [19, 48]), but is nevertheless worth addressing. Additionally, participants' understanding and interaction with each device may evolve throughout the stimulus irrespective of a training phase. There is a potential issue of reverse inference in ratings: interacting with the device might lead participants to infer their own engagement rather than the device reflecting their true experience.

Secondly, each device has unique movement requirements and may capture a specific but different component of emotional involvement. The BB involves movement of the entire hand to counter the physical resistance of the ball, whereas the slider just involves thumb movement. This diversity in input mechanism underscores the need to take care when analysing and interpreting the resultant data. While there is recurring coherence with both methods with the physiological signal, the self-report potentially contributes an interpretative dimension to engagement. Further, the interpretability of EDA should to be treated cautiously [8]. Hence, rather than fueling a discussion on the nature of engagement, it should be discussed how engagement is measured and interpreted [11].

Both feedback devices are susceptible to - and even encourage - fidgeting, a behaviour previously associated with boredom, disengagement and frustration in time-based stimuli [17, 43]. While our present study demonstrated a systematic relationship between self-report and physiology, we did not explicitly address fidgeting. Still, it is crucial to investigate whether the use of the devices reduces or enables the need to fidget. Further, engagement varies based on individual factors such as personality types, neurodivergence, learning styles, and past experiences which the present study did not consider [49]. Perhaps the squeezing is intuitive to some and abstract to others.

Lastly, a major factor in watching dance is expertise. Vincs *et al.* demonstrated that dance expertise and engagement are linearly related [47]. The results of the GDSI show that expertise in watching dance is moderate throughout the current sample leaving open the question of how professional dancers or perhaps film-makers might respond.

5.3 Conclusion

This study aims to demonstrate and discern the utility of two real-time continuous self-report devices while correlating them with physiological data. The squeeze BB received more favourable ratings over the slider. The BB and slider responses are weakly to moderately correlated with the arousal inferred from the EDA. Time-series analysis did not clearly identify the more suitable self-report device for measuring emotional involvement in the specified context. Nevertheless, both data sets provide more fine grained information than traditional methods of assessing arousal. Further investigation is needed to ascertain how these devices might be used over longer time-periods, and when deployed in real-world studies like live performance.

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