Squeeze The Pain Away: Using a Wireless Ball to Measure Efforts to Reduce Other's Pain Expressions in VR

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Abstract

Virtual reality has often been used as a tool to study empathy. However, few studies have explored users' willingness to make physical effort to actively reduce others' pain. We developed a pipeline that integrates a wireless stress ball into a VR environment. This device measures continuous grip force, enabling participants to adjust a virtual character's pain expressions through squeezing: the harder they squeeze, the less intense the pain expressions become in real-time. This shifts the participants' focus from passive observation to active participation. Our results indicated that participants were highly motivated to use the ball to reduce virtual characters' pain and showed particularly high use of effort in the first 10 seconds of a 15-second trial. Eye-tracking data revealed that participants focused primarily on pain-related facial features, consistent with previous pain decoding studies. Our effort-based approach offers a novel method to study pain perception.

CCS Concepts

• **Human-centered computing** → **Virtual reality**; **Haptic devices**; **Systems and tools for interaction design**; **Empirical studies in HCI**; **HCI design and evaluation methods**.

Keywords

real-time measures, engagement, pain, EDA, squeeze interaction, perception

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1 Introduction

Virtual reality (VR) has increasingly been used in pain-related research and therapy, leveraging its immersive nature to manipulate sensory and cognitive processes. For instance, VR has been employed to distract patients from acute pain [19], simulate empathetic experiences [50], and explore the neurobiological underpinnings of pain perception [52]. While these approaches often focus on how VR environments influence self-pain, fewer studies have used VR to study how users perceive and are motivated to reduce pain from others [55]. This study investigates the potential of a novel VR input device based on an effort-based squeeze interaction, designed to enable intuitive, pressure-sensitive ball control. While this input method has broad applications, pain-related scenarios provide a particularly relevant context to investigate its potential. To explore its feasibility, we conduct a case study on pain reduction, specifically aimed at assessing how this interaction can be used to quantify and examining how users engage with this interaction to alleviate others' discomfort in VR.

1.1 Squeeze Ball Interaction

Squeeze interaction is an intuitive and expressive technology that allows soft, deformable materials to serve as input [47], enabling users to engage with virtual environments through physical manipulation [27]. By simulating multidimensional physical feedback, squeeze interaction builds on traditional VR control methods that primarily rely on precise tools like controllers and buttons. Recent studies have shown that squeeze-based interactions can foster a more embodied and natural experience for users, improving immersion and accessibility [53, 54].

While squeezable inputs in VR are relatively rare, ball-shaped devices stand out among the limited options. Their compact, ergonomic shape provides consistent tactile deformation-based feedback, making them well-suited for controlled input and repeated use, while also enabling more precise pressure data collection compared to softer alternatives such as cushions and plush toys [33] and conventional VR controller inputs. The concept of squeezing also as a therapeutic action has long been associated with stress balls. Stress balls are widely recognized as non-pharmaceutical tools for managing stress and discomfort [41]. The physical feedback provided by squeeze interaction has been linked to self-generated touch, a sensory mechanism known to regulate anxiety and support pain relief [5, 59]. Importantly, the ball squeeze gesture is a natural, intuitive action with low learning cost, making it a simplistic, training-free, and care-free hand gesture suitable for everyday interaction with technology [33]. This highlights the potential of physical actions, like squeezing, in creating a more interactive and empathetic VR experience.

1.2 Virtual Character and Pain Expressions

1.2.1 Pain Expression. Observable pain-related expressions are universally recognized as reliable indicators of discomfort, making them essential for both pain communication and diagnostic purposes [28]. Xiong et al. [58] have shown that pained facial expressions alone can activate brain regions related to pain empathy. Also, clinicians frequently rely on observable cues, especially facial expressions [8, 12], to assess patients' pain when self-reporting is unavailable or impractical, such as critically ill, individuals with cognitive impairment or young children[3, 31, 32]. However, the subjective nature and potential inaccuracies of perceiving others' pain present significant challenges. These challenges have driven systematic research into understanding pain through facial activities, including the development of pain expression archives and analytical tools to standardize and improve assessments. Databases documenting real pain expressions images or video, such as those by Lucey et al. [36] and Fernandes-Magalhaes et al. [17], have provided researchers with useful resources for studying how other's pain is expressed and perceived.

In automated measurement, significant research has focused on the integrated decoding process using the Facial Action Coding System (FACS) [14] to analyze pain-related facial patterns [35, 48, 57]. Several studies [8, 36] have utilized the Prkachin and Solomon pain intensity (PSPI) metric [44] to define pain by action unit (AU). Most of these studies focus on analyzing real human faces, such as decoding facial movements [7, 17], distinguishing genuine from feigned pain [2], or pain detection and estimation [48].

With the growing use of virtual reality environments in pain-related research, designing realistic facial expressions for virtual characters has become increasingly important. For example, Meister et al. [38], Tolba et al. [49] explored the role of virtual characters as proxies for observing and interpreting others' pain. However, there is a noticeable lack of comprehensive research on morph target animation (also known as blendshapes), one of the most commonly used techniques for virtual character facial animation [1, 37, 45]. This technique, closely linked to the FACS, enables the creation of detailed and expressive facial movements. Therefore, decoding and replicating facial expressions in virtual characters presents a highly promising avenue for studying pain in virtual environments.

1.2.2 Virtual Character as Others in VR. Building on their ability to display realistic facial expressions, virtual characters offer unique opportunities to study how people perceive and respond to others' pain. When experienced within a VR environment, these interactions become more immersive and dynamic, as VR enhances social engagement by enabling virtual contact with others [15] while providing better experimental control, reproducibility, and ecological validity [42]. This approach eliminates ethical concerns associated with exposing individuals to real pain [21]. The flexibility makes virtual characters valuable tools for investigating complex phenomena such as empathy [6], bias, and pain perception [30], especially through dynamic, multi-modal cues. For example, incorporating facial pain expressions with trunk movements enhances the perceived intensity and realism of pain [51].

However, research involving virtual characters as tools for observing and interpreting others' pain remains limited, with most studies conducted in observation-based settings [6, 51]. The use of virtual characters in immersive VR environments for studying the perception of others' pain is even less explored. While numerous studies have explored the reasons behind individuals' desire to help alleviate others' pain [21–23, 29], altruistic behaviours [34, 56] and prosocial efforts to reduce pain [11, 22] in neuroscience and psychology, to our knowledge, no existing research has directly measured participants' motivation to reduce others' pain through interactions with virtual characters. VR presents a unique opportunity to systematically measure prosocial motivation and behaviour by enabling precise control, repeatable conditions, and adaptable social interactions across diverse and ecologically valid VR-enabled contexts. It also serves as an effective tool for studying pain-related emotional and social cues such as facial expressions and body movements, and deepens our understanding of how individuals perceive and respond to others' pain in dynamic, controlled environments. Despite this potential, there remains a lack of studies employing behavioural data-collection tools to quantitatively measure how willing individuals are to actively exert effort in pain scenario.

To address this gap, we developed a budget-friendly squeeze interaction device—a stress ball—that records continuous grip force data and can function as an alternative input device for VR controllers. In our experiment, the device allows participants to directly modulate the pain expression of a virtual character in a VR environment, in real-time: **the stronger the squeeze, the less intense the avatar's pain expressions**. This approach introduces a new way to study pain empathy, using physical action to influence the perceived experience of others' pain. Additionally, by integrating continuous physical feedback into a VR context, our prototype has the potential to combine with other continuous data commonly collected in pain studies, such as electrodermal activity and heart rate [18, 40], enabling cross-analysis and time-based investigations.

2 Implementation pipeline

We have carried out hardware modifications on a stress ball to make it function as an external device for VR applications. Based on this design, we demonstrate technical pipeline functional details in Figure 1 how the stress ball is made and used in a VR scenario to enable participants to "relieve the pain" for virtual characters.

2.1 Ball Hardware Functions: Squeeze Interaction

2.1.1 Pressure Sensor. The pressure sensor is a critical component of this device. During the initial design phase, various pressure sensors with different shapes and capacities were procured and tested, ranging from small-scale sensors (50g–2kg) to larger ranges (500g–20kg, 200g–30kg, and 5kg–50kg). Considering the males' peak median grip was 51 kg and females 31 [13], the final selected sensor was the MD30-60, which has a range of 5–50kg and a diameter of 30mm, ensuring it accommodates the majority of users' grip strengths.

2.1.2 WiFi-enabled. To meet portability and wireless functionality requirements, multiple compact WiFi-enabled boards were evaluated, including various forms of ESP32, Raspberry Pi, and Arduino. The Seeed Studio XIAO ESP32S3 was ultimately selected due to its compact size (21mm × 18mm), compatibility with a 1200mAh 3.7V lithium battery, and other components that enabled easy integration into a stress ball. Its additional antenna module supports 2.4GHz Wi-Fi, ensuring stable OSC signal transmission and high-frequency communication.

2.1.3 Ball Data Transmission and Force Conversion.

Data Transmission System. A customised OSC message system was developed for transmitting and receiving data from the device. Utilising the XIAO ESP32S3 board's 2.4GHz Wi-Fi functionality, the system was configured to broadcast data at 100Hz. In Unity, multithreaded execution minimised latency and enabled seamless real-time data collection via the Threading function. Fixed update intervals facilitated the stable logging of 60 data points per second. Additionally, to address fluctuations in raw data, a "digital filtering" algorithm was implemented directly on the XIAO board. The system calculates and broadcasts the average of the most recent 10 readings at a 100 Hz frequency.

Mapping Digital Readings to Physical Effort. Professional force-measuring instruments secured the device between two durable acrylic plates, chosen for their stability and consistent surface properties to minimise measurement errors. Three repeated measurements recorded Newton values and corresponding Ball readings, ensuring consistency.

2.2 Virtual Character Creation: Pain Animation

2.2.1 Virtual Character Modelling. Four virtual characters (Black Female, White Female, Black Male, White Male) were created using Character Creator 4 (CC4). To ensure consistent baseline geometry, we started with the same white model template, adjusting skin texture and modifying facial features based on user feedback to reflect different ethnicities. This approach ensured demographic diversity while maintaining uniformity in structural design.

2.2.2 Pain Animation: Facial Expression and Body Movement. We selected 16 top-rated real pain (8 male, 8 female) videos from the PEMF database [17] and used iClone8 and the AccuFace plugin to convert the video clips into virtual characters' facial expressions animation sequences (Figure 2). Refer to FACS-based pain studies in Section 1.2.1, where the PSPI FACS pain scale, the only metric capable of defining pain on a frame-by-frame basis [36], is used to map ARKit blendshapes [1] when modifying pain expressions (Figure 3). We also added body idle animation on virtual characters to avoid stiffness. Furthermore, an "ouch" pain sound is triggered at the onset of the pain animation. Additionally, we wrote a script to ensure the avatar maintains eye contact by dynamically targeting the participant's head position.

2.3 Alternative VR Input Device Combined with Eye Tracking

The stress ball device was programmed within a Unity VR environment to function as a real-time alternative to traditional input mechanism, such as sliders [47] and buttons [39]. We designed a *continuous Interaction* (percentage-based continuous holding trigger or sliding and drag action) and a *discrete Interaction* (click and select action coop with eye-tracking or called Gaze-Pinch Interaction [43]). We create a script to record eye-tracking data to explore how participants direct their gaze toward key pain-related facial regions of the avatars. Collision blocks were placed on specific pain-related action units (see section result) of each avatar's face to detect gaze patterns according to previous studies [7].

3 Methodology

3.1 Participants

This study was reviewed and approved by our ethics committee (omitted for anonymity). An online pilot study was first conducted on Prolific with 128 participants (64 men and women each, 64 white and black ethnicities each) to validate our animation stimuli. Then, for the VR study, a total of 36 individuals (17 male, 18 female, and 1 non-binary), aged between 22 and 45, from diverse demographic backgrounds participated on a completely voluntary basis, without receiving any form of compensation. All participants completed a consent form regarding the use of their data and provided verbal consent, which was documented in written records, for their images and videos to be used in the publication.

3.2 Apparatus

The experimental setup included a laptop running Unity 2022.3.33 with the Meta Interaction SDK, which served as the platform for the virtual environment. Participants interacted with the system using a Quest Pro VR headset, which featured integrated eye-tracking capabilities for capturing gaze behaviour. For pain-related interactions, the stress ball (detailed in the Implementation section) was used, allowing participants to engage in the pain task. Additionally, physiological data such as heart rate, electrodermal activity (EDA), and skin temperature were recorded using an Empatica EmbracePlus smartwatch [20] to monitor participants' biodata throughout the experiment.

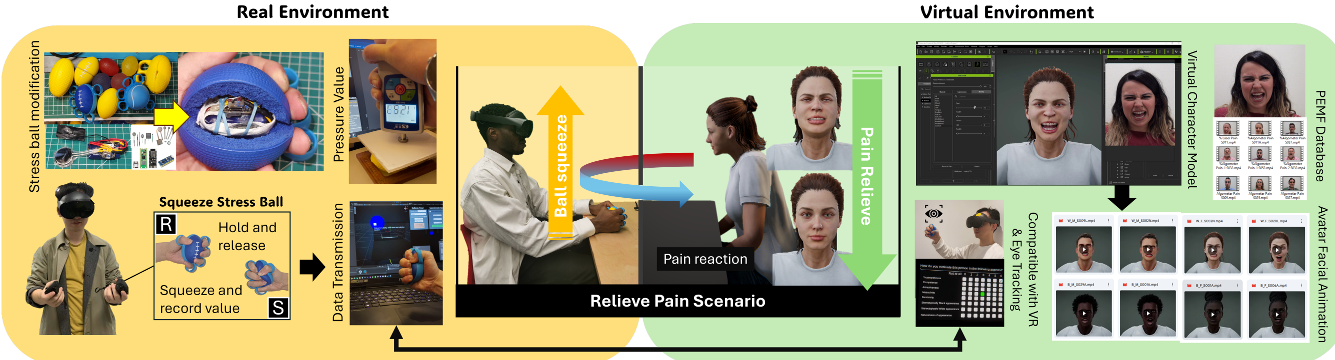

Figure 1: Technical Pipeline: Implementation of ball-controlled avatar actions in a pain scenario in VR

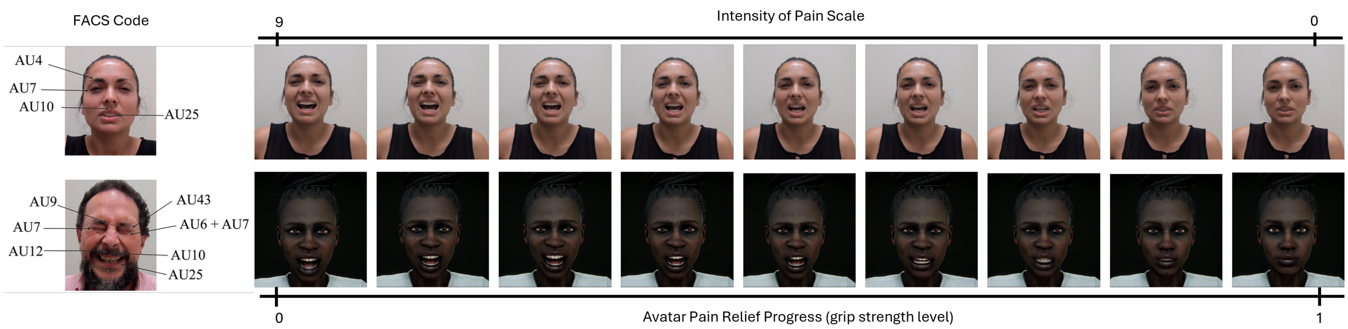

Figure 2: Pain E-motion Faces Database (PEMF) video transient pain expression [17] and corresponding virtual character animation

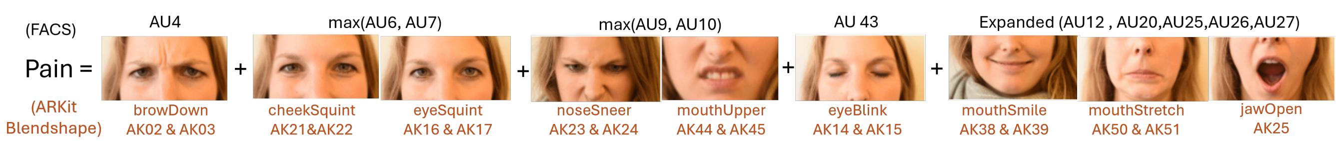

Figure 3: Pain animation adjustment reference: ARKit blendshape & PSPI mapping (more details in Appendix)[8, 16, 36, 44]

3.3 Experimental Design

As shown in Figure 4, we run an online video evaluation pilot study. There are participants who evaluate 16x4 animations. we selected the top-rated (intensity of pain) 8 animations for the VR study. Serving as the primary phase of the VR study, our experiment was conducted within a pain relief scenario. The experimental procedure began with a consent session where participants were informed about the project objectives, procedures, and tasks. Participants then were equipped with an Empatica smartwatch and a VR headset. Inside VR, a calibration phase was performed, which included eye-tracking calibration and the configuration of the stress ball. During this phase, participants were trained in the proper use of the stress ball and their individual minimum and maximum grip strength thresholds were measured and recorded to tailor their specific capabilities.

The pain relief phase was based on 4 virtual character conditions the 8 pain animations mentioned in Section 2.2. These animations were divided into Group A (S044A, S027A, S006A, S028L) and B (S020L, S001A, S029A, S052N) [17]. Each group session corresponds to one of the animation groups (4 × 4 trials) resulting in a total of 32 trials (2x4x4) for each participant. The trial order was randomized using a Latin Square design to balance sequence effects. Before the first trial of the pain relief study, participants were shown the following message: "You are about to see a person in pain. By squeezing the ball firmly, you can help to relieve their pain. Conversely, if you release your grip, their pain will return." During each trial, participants performed a 15-second squeeze pain relief task. Considering fatigue from prolonged squeezing, each trial was followed by a 15-second rest, and a 60-second break was provided between sessions. Additionally, the stress ball's maximum threshold coefficient was adjusted to 1.1 times in session A to accommodate initial strength and reduced to 0.95 times in session B to minimize strain from extended use.

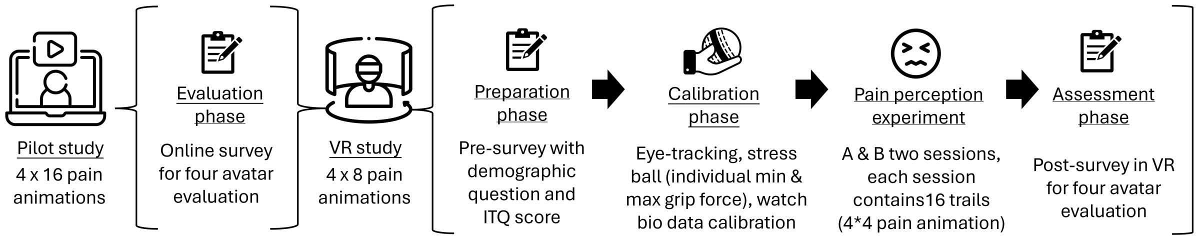

Figure 4: Experiment Procedure: Pilot and VR studies

3.4 Measurement

In the pilot study, we used subjective reporting questions (9-point Likert scales) for participants to rate the intensity of virtual characters' pain in the video (from 0, "Not at all intense", to 8, "Most intense possible"). In the VR study, stress ball force data, and eye-tracking from the VR headset were collected. Continuous data were logged at 50 frames per second. Using calibrated minimum and maximum grip strength values, participants' efforts were mapped to a pain animation range from 0 (painful) to 1 (not painful), representing the percentage of effort relative to their maximum grip strength . Eye-tracking data recorded participants' gaze rays and mapped them to predefined collision areas on the virtual characters' faces. The data captured whether participants looked at non-character areas, the upper body, or the face, with the face further divided into pain-related feature areas, including the eyebrows, eyes, nose, mouth, and other parts such as the forehead and cheeks.

4 Results

4.1 Pain Relief Behaviour

The time-series data in Figure 5 shows participants' squeeze effort responses during 15-second pain relief trials. Figure 5A illustrates the overall trend of pain relief effort ($E_{\%}$ mean= 0.665) and its relationship to the percentage of pain animation, as can be seen, effort increases starting from zero and peaks around 3–4 seconds before transitioning into a sustained effort phase ($E_{\%}$ mean= 73.8%). Using the sixth second as an example, 85% of all trials maintained $E_{6s} > 60\%$, while 60% reached $E_{6s} > 80\%$.

We further explored the relationship between timing and effort by first calculating the mean effort relative to the threshold for three 5-second bins (0-5, 5-10, 10-15). We then ran a 3 (time bin) x 2 (block) repeated measures ANOVA. This analysis revealed no effect of block ($F(1,35)$=3.83, p=.058, η_p^2 = .099. However, there was a significant effect of time bin, ($F(1.12,39.28)$=4.77, p=.031, η_p^2 = .12). The interaction was not significant, ($F(1.16,40.70)$=2.18, p=.144, η_p^2 = .059). Post hoc tests identified the effect of the bin was driven by the fact participants used significantly more effort in the first 5-second bin (EMM=85.3, SE=3.28) compared to the last 5-second bin (EMM = 81.5, SE = 2.40, $t(35)$=7.35, p=<.001). In contrast, there was no significant difference between the effort in the second bin (EMM = 84.9, SE = 2.63) and either the first or third bin (see Figure 5C).

4.2 Eye-Tracking Gaze Data

The eye-tracking data showed clear patterns in where participants focused their attention in Figure 6. Overall, participants allocated the majority of their gaze (74%) to the head region, followed by non-character areas (16%), and the body (10%). Within the head region, the gaze further concentrated on specific facial features. The nose accounted for the highest proportion of gaze (19%), followed by the mouth (15%), and eyebrows (8%). Notably, participants' gaze on the eyes was relatively low, with 4% directed at the left eye and 3% at the right eye. Cumulatively, nearly half of the gaze (49%) was directed at facial features associated with the virtual character's pain expression (which included facial actions such as an open mouth, furrowed eyebrows, tightened nose, and squinting eyes,), highlighting an attentional focus on emotionally salient areas.

5 Discussion

5.1 Effort-Driven Squeeze Interaction in Pain Perception

The stress ball's tactile design makes it an intuitive tool for pain relief, requiring no training and offering real-time feedback [47]. One participant noted, "There's no learning curve – you can start using it straight away." Unlike traditional pain assessment [32], like Numeric Rating Scale (NRS) or Face Pain Scale (FPS) [4, 24], the stress ball aligns naturally with pain relief actions like clenching fists or gripping objects [46]. Another participant shared, "If I were holding a loved one's hand in pain, I'd naturally squeeze back." This combination of effort and empathy makes the stress ball as a good tool for managing pain in both research and practical settings.

The stress ball was designed to revert to a painful expression when released, requiring participants to actively decide how much effort they were willing to exert to ensure that the virtual characters would not show signs of pain. As shown in the 15-second trend in Figure 5B, participants demonstrated a high level of willingness to expend effort in order to reduce the characters' pain expressions with participants consistently reaching over 80% of the maximum threshold and maintaining that level of effort across the entire 15-second trial although with some decrease of effort in the last 5 seconds of the trials.

Our findings align with prior research highlighting the role of effort in driving motivation and prosocial behaviours. Studies on effort-based decision-making paradigms [10] and prosocial incentives, such as charitable giving [26], have shown that the willingness to exert effort reflects deeper engagement and motivation. Similarly, our results suggest that physical effort serves as an active mechanism to engage participants in alleviating others' pain. Active, effort-based paradigms not only provide ecological validity but also shift the focus from passive, detached evaluations to meaningful

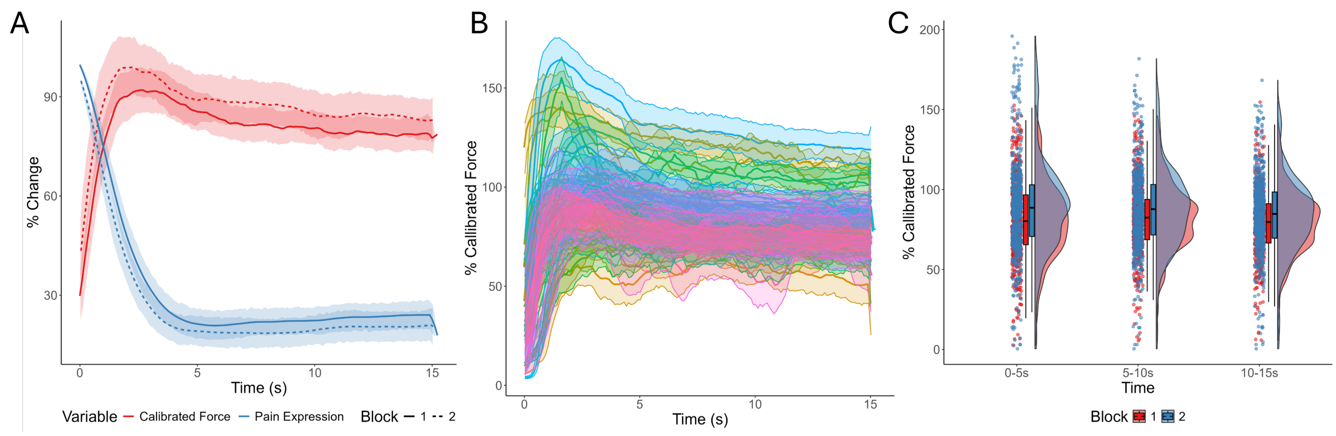

Figure 5: A) Mean % of calibrated effort used and pain expression on virtual characters across all trails by block(shading represents 95% confidence intervals. B) Mean % of calibrated effort used averaged across all trials. C) Mean % of calibrated effort across 5-second bins by block.

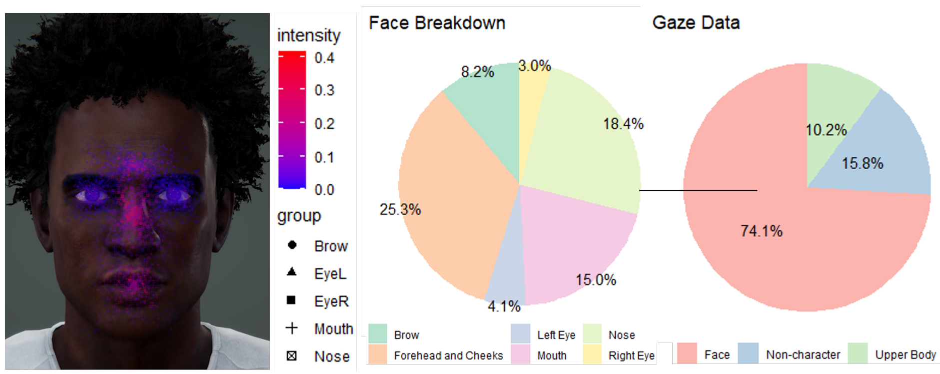

Figure 6: Gaze percentage proportion on the avatar during the trials. The left face heat map illustrates the intensity of critical pain-related feature areas (e.g., furrowed brows (AU4), squinted eyes (AU7), lips raise (AU10) [44]).

actions in pain-related contexts, offering deeper insights into the dynamic interplay between effort-driven and empathy.

5.2 Attention to Facial Cues in VR

With six degrees of freedom (6DoF), participants can observe and interact with virtual characters' pain expressions from multiple angles, capturing richer details of facial movements. This provides a significant advantage for research, as VR enables real-time tracking of gaze patterns on specific facial action units.

Participants spent nearly half of their gaze time (49%) on observable pain-related expressions. These gaze patterns closely align with the PSPI formula [16, 44], where key action units—including the mouth (15% - AU10, AU12, AU20, AU25, AU26, AU27), eyebrows (8.2% - AU4), eyes (7% - AU6, AU7), and nose (18.4% - AU9, AU10)—carry the most information about pain. This alignment confirms that participants naturally focused on the most relevant facial regions for decoding pain.

Furthermore, gaze behaviour data can serve as a supplement to FACS coding. By leveraging proportional gaze distribution, future studies could design decoding tasks that assign weight of action units with more pain-related information, thereby improving the precision and depth of pain analysis.

6 Conclusion

In this work, we developed a technical pipeline that integrates a wireless stress ball device into a VR environment, enabling squeeze-based interaction to study effort-driven pain modulation. This pipeline supports both discrete (in combination with VR eye-tracking) and continuous interaction modes, demonstrating the stress ball's capability as a straightforward alternative to traditional VR inputs such as sliding or clicking. The effort-based interaction motivated users and shifted pain-related research from passive observation to active participation, creating the potential for reducing biases in pain perception and fostering motivation through physically engaging interactions. As part of our pipeline, we mapped pain-related facial action units to blendshapes, enabling the creation of realistic animations and pain-related decoding. This serves as a preliminary result for future researchers aiming to conduct similar experiments in various real-world pain scenarios by using virtual character in VR context. In terms of measurement, our squeeze ball interaction offers a possibility to quantify effort in pain empathy with continuous data. Future research could build on this approach by integrating it with pain studies in neuroscience [9, 58, 60], along with biofeedback analysis, to further explore how people respond to others' pain. In summary, these findings highlight the potential of VR-based pain research to move beyond passive paradigms, enabling more interactive and effort-driven approaches to studying and addressing pain. By integrating effort-based interventions, virtual character and VR social interaction provide a practical way to study how people perceive and respond to pain in more immersive, interactive and detailed ways. Ultimately, this approach could broaden research in VR, psychology, and therapy, even pain policy decisions [25] in future studies.

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A ARKit Blendshape Code and Pain-related FACS Mapping

Index	Blendshape (AK)	FACS (AU)	Description	Facial Muscle
A01	browInnerUp			
A02	browDownLeft	AU4	Brow Lowerer	Depressor Glabellae, Depressor Supercilli, Currugator
A03	browDownRight	AU4	Brow Lowerer	Depressor Glabellae, Depressor Supercilli, Currugator
A04	browOuterUpLeft			
A05	browOuterUpRight			
A06	eyeLookUpLeft			
A07	eyeLookUpRight			
A08	eyeLookDownLeft			
A09	eyeLookDownRight			
A10	eyeLookOutLeft			
A11	eyeLookInLeft			
A12	eyeLookInRight			
A13	eyeLookOutRight			
A14	eyeBlinkLeft	AU43		Relaxation of Levator Palpebrae Superioris
A15	eyeBlinkRight	AU43		Relaxation of Levator Palpebrae Superioris
A16	eyeSquintLeft	AU7	Lid Tightener	Orbicularis oculi, pars palpebralis
A17	eyeSquintRight	AU7	Lid Tightener	Orbicularis oculi, pars palpebralis
A18	eyeWideLeft			
A19	eyeWideRight			
A20	cheekPuff			
A21	cheekSquintLeft	AU6	Cheek Raiser	Orbicularis oculi, pars orbitalis
A22	cheekSquintRight	AU6	Cheek Raiser	Orbicularis oculi, pars orbitalis
A23	noseSneerLeft	AU9	Nose Wrinkler (also shows slight AU4 and AU10)	Levator labii superioris alaquae nasi
A24	noseSneerRight	AU9	Nose Wrinkler (also shows slight AU4 and AU10)	Levator labii superioris alaquae nasi
A25	jawOpen	AU25, AU26, AU27	Lips part, Jaw Drop, Mouth Stretch	Depressor Labii, Relaxation of Mentalis (AU17), Orbicularis Oris, Pterygoids, Digastric, Masetter; Temporal and Internal Pterygoid relaxed
A26	jawForward			
A27	jawLeft			
A28	jawRight			
A29	mouthFunnel			
A30	mouthPucker			
A31	mouthLeft			
A32	mouthRight			
A33	mouthRollUpper			
A34	mouthRollLower			
A35	mouthShrugLower			
A36	mouthShrugUpper			
A37	mouthClose			
A38	mouthSmileLeft	AU12	Lip Corner Puller	Zygomatic Major
A39	mouthSmileRight	AU12	Lip Corner Puller	Zygomatic Major
A40	mouthFrownLeft			

A41	mouthFrownRight			
A42	mouthDimpleLeft			
A43	mouthDimpleRight			
A44	mouthUpperUpLeft	AU10	Upper Lip Raiser (also shows slight AU25)	Levator Labii Superioris, Caput infraorbitalis
A45	mouthUpperUpRight	AU10	Upper Lip Raiser (also shows slight AU25)	Levator Labii Superioris, Caput infraorbitalis
A46	mouthLowerDownLeft			
A47	mouthLowerDownRight			
A48	mouthPressLeft			
A49	mouthPressRight			
A50	mouthStretchLeft	AU20	Lip Stretcher	Risorius
A51	mouthStretchRight	AU20	Lip Stretcher	Risorius

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