Assessing the validity of wearable technology as game input for exergames

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***Abstract*—The use of wearable technology in game-based approaches is a topic of research that has gained growing interest over the past decade, which in part can be attributed to the increased adoption of wearable technology. Our paper investigates the validity of off-the-shelf wearable technology as game input, focusing on exergames as an application. Our paper explores how off-the-shelf wearable technology compares with medical grade wearable technology and consider the potential for applications based on our results, highlighting how a variability in measurements may affect the applicability of the technology for serious games in health. Our paper also investigates the potential for the adoption of wearable-driven exergames while also considering the participant's insight on the usability and fun of the gaming experience. We highlight the areas for future work and identify the need to continue assessing wearable technology for game-based applications and for future work to investigate the requirements for wearable-driven game experiences when applied to younger age groups.**

***Index Terms*—wearable technology, heart rate, sensor validation, exergames, serious games, games for health**

I. Introduction

Wearable technology considers a wide range of devices, including smartphones, smartwatches and other devices that can be categorised under the umbrella term of mobile computing [1]. Wearable technology can be considered to be widely accepted by the general public, given the units sold [1]. Similarly, the range of consumer wearable devices has expanded [2], further accelerating the adoption of the technology. These factors have promoted new research to consider how wearable technology may improve healthcare applications [2], monitor vulnerable adults [3] and introduce new experiences in exergaming [4].

In the field of game-based solutions, wearable technology has been utilised to help monitor biofeedback during gameplay [5], towards designing adaptive gaming experiences [6], and towards biofeedback-controlled game experiences [2], [4]. Commonly, the application for these game-based approaches centres around healthcare and the wider academic discipline of serious games for health. Games for health harness the immersive qualities of game experiences and apply them to health care applications either towards preventative care [7]–[9], rehabilitation [10]–[12] or more [13].

While new research directions in wearable technologies for games and game-based approaches are being noted in the literature [14], there is limited work that considers the applicability of wearable technology [15]–[17], with a focus on the validity of the readings reported from the sensors and how significant a level of inaccuracy in the sensors readings may be towards a specific game experience.

Our paper focuses in particular on smart trackers, such as heart rate monitors and smartwatches in relation to wearable technology. With previous research already considering how games may use wearable technology as game input [4], our paper presents how viable wearable technology may be as an option for sole game input and sets the following research questions in this paper:

- How valid are the measures of heart rate from an off-the-shelf smartwatch, and how do they compare with medical-grade equipment?
- How would people perceive a game experience based on wearable technology as sole input?

We present our findings around these questions, using a combination of data sourced while playing a game controlled through heart rate alone, heart rate data from a medical-grade sensor and questionnaire data post-game play sourcing the opinions of each participant.

II. Background

The growth in the popularity and adoption of wearable technology [14] has led to new research considering how

[1]https://tinyurl.com/bdd7zeta, Accessed 06/03/2024
[2]https://www.linkedin.com/pulse/global-wearable-technology-market-size-share/, Accessed 06/03/2024

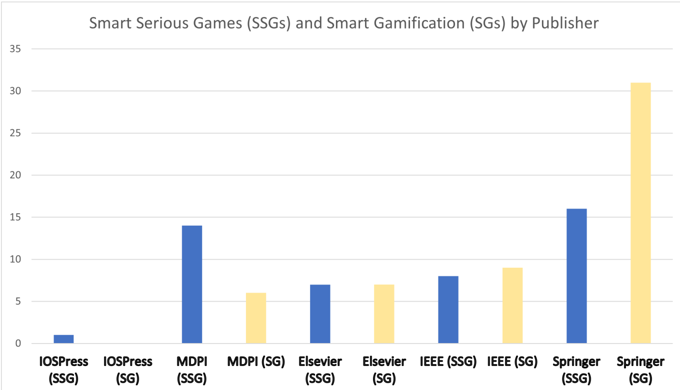

Fig. 1. Literature return from Google Scholar when searching for Smart Serious Games and Smart Gamification as terms, presented per publisher. Dark color represents the data for Smart Serious Games and the light colour represents the data for Smart Gamification.

wearable technology may benefit a wide range of application areas [18]–[20]. Our paper focuses on the impact wearable technology is having on games, gamification, serious games, and game-based approaches in the following section.

Research into wearable technology for game experiences relates to a larger line of research that investigates how sensor interconnectivity may improve existing solutions and improve our understanding in the applications for serious games and gamification [21]. Similarly, research has considered how the Internet of Things (IoT), which describes the sensor ecosystem that enables machine to machine communication and internet connect services and devices to coexist [22], may interact and integrate with serious games and gamification [23]–[26].

As research into sensor-based game experiences continues, it is crucial that future research considers the limitations of the hardware and software that allow for the direct connectivity between game experience and body, not solely from a game experience perspective but from the validity of the solutions being developed for serious applications.

A. Sensors and Games

Sensor technology has increased in availability and adoption over recent years, which in part has led to an increase in research activity that investigates how sensors may improve gaming experiences or help create new ones [4], [14], [21]. IoT has enabled *smart* technologies to improve healthcare approaches [27] but has also furthered our understanding in sensor connectivity [28].

The combination of Serious Games and Gamification with IoT has been termed as Smart Serious Games and Smart Gamification respectively [26]. While these terms are not seen as frequently in published literature, as seen in Fig. 1, they describe the combination of IoT and game-based approaches extensively, and as such, these terms are considered in our paper. Smart Serious Games has seen the development of applications for education [23], exercise [4], healthcare [13], and more. Similarly, Smart Gamification has seen research consider new approaches to tourism incentives [29], shopping [30] and others. Sensor integration with game experiences is not limited to academic literature alone. Sony has used sensors to help improve player input when using the VR2 [3]. In addition, Sony also patented Heart sensors into PlayStation controllers [4]. HypeRate, have created software that streamline the connectivity of wearable technology [5]. Based on the trends seen in the games industry and academia, we envisage further developments and game experiences that integrate closely with biofeedback.

B. Wearable technology in games

Wearable technology in games has seen research consider how the data extracted from sensors may provide improved data insights for healthcare applications and improved game experiences during gameplay in games for health. Research into wearable technology that monitored heart rate during gameplay noted the significance of biofeedback on improving immersion [31]. Similarly, research into game mechanics that could be tailored to biofeedback sourced from smartwatches to feedback and improve participant performance [32] in an exergame application.

While the research into wearable technology and game experiences is indicating promise in new application areas, we highlight the significance of appropriate testing of wearable technology and biofeedback data when applied towards game-based experiences. Research into the validity of wearable controlled games shown off-the-shelf technology can be used effectively for monitoring wrist range of motion [15]. A review on the validity of measures from a range of wearables reported mixed results, depending on the manufacturer of the wearable [17], highlighting the need to contextualise the readings obtained from wearable technology when embedded into game experiences. Similarly, research has considered our understanding of the generalisability of the classification of heart rate signals, which can be used towards adaptivity in games experiences [33]. Our research builds on the existing knowledge by considering the validity of the Fitbit wearable for heart rate driven games.

III. Validating a wearable device for games input

Our paper considers how the presented methodology may generalise and reproduce the results presented . Firstly, the parameters for validating the technology were set. Our experiments focused on the validity of the heart rate signals obtained from a Fitbit Versa 2 [6], as this is the same sensor used in an early prototype of a wearable controlled exergame [4].

The related exergame game was produced by Henry et al. [4], called Cardia. The game is driven solely by the user's heart rate, while they are pursued by a monster, in which the

[3] https://blog.playstation.com/2023/02/06/playstation-vr2-the-ultimate-faq/, Accessed 05/03/2024

[4] https://www.freepatentsonline.com/20200054940.pdf, Accessed 13/03/2024

[5] https://www.hyperate.io/, Accessed 22/03/2024

[6] https://www.fitbit.com/global/us/products/smartwatches/versa, Accessed 11/03/2024

higher the heart rate, the faster the player will move. The game has 2 states:

- Win state: the player keeps their BPM high enough to outrun the monster and get to the exit.
- Lose state: the player could not maintain a high BPM, and the monster caught the player.

Players will also have to run on the spot to charge a jump in which the monster will still follow. This is to encourage the player to move faster. For full details, see the original works [4].

The same exergame was used as a vehicle for measuring heart rate over a period of time during exertion to determine the feasibility of the wearable device as game input. Secondly, a medical grade sports sciences device was used that is used in sports sciences,accounting for the nature of the game experience used in the experiment. The Polar H10 heart rate sensor [7] met the requirements of the study and allowed us to extract the heart rate data into CSV, enabling us to compare between the Fitbit Versa 2 and the Polar H10 heart rate measures.

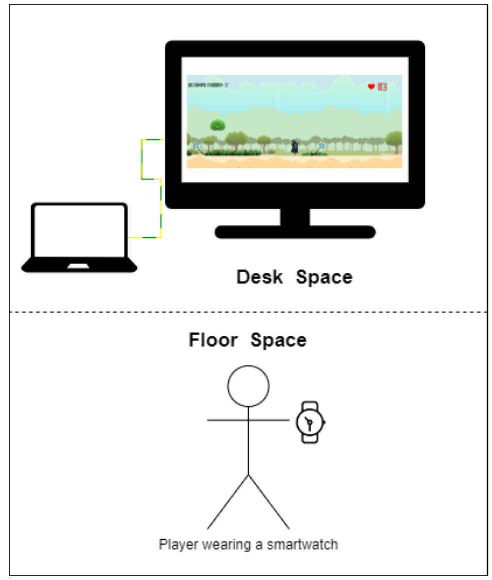

Fig. 2. An illustration of the physical set up of the game detailing how the game is played

A. Participant Recruitment

Participants were recruited through a play test sessions, one held at Coventry University and an identical play test session held at Manchester Metropolitan University, followed by smaller play test sessions held during the first academic semester of the 2023/2024 academic year at Manchester Metropolitan University. We aimed to recruit adults (aged 18 and above) rather than target any particular age band to generalise the data outputs from the experiment. Participants were approached through social media posts on LinkedIn and Twitter/X, emails, and through a taught unit that promotes industry engagement in the second year of all computing-related undergraduate degrees. In total, we recruited *n=14* participants across all play test events. We recognise that this number limits how generalisable our insights may be, and as such, further play test events are being carried out in May 2024. Any further findings from the latest round of experiments collectively in a future, expanded publication.

B. Experiment Protocol

At the beginning of the experiments, participants were provided with a participant information sheet detailing the experiment process and a consent form. Following consent, participants were asked to wear the Fitbit Versa 2 and the Polar H10 devices, after receiving guidance on how to wear the devices. Once participants stated they were ready to proceed, we placed them in front of a TV with Cardia running and synchronised the start time of measuring the data between both devices to the best of our ability. Fig 2 illustrates the set up of the experiment in the physical space.

At the end of the experiment, the heart rate signals measurements from the Polar device were stopped to create as similar a data long between the two sensors as possible. The Fitbit auto stops recording on the game's completion. After participants removed the wearables from their body, they were asked to complete a questionnaire that sourced their opinions on the usability and fun aspects of the game experience and on the adoption of the technology. The three key areas were considered to examine whether the game experience distressed participants, whether the combination of wearable technology and game experiences are positively received by participants and whether the concept of a heart-rate driven game would be welcomed by the participants. The data from the questionnaires was also analysed to test if they provided further insights into the sensor-sourced data.

IV. Data Processing

Data from the related experiments were processed in two stages. In the first stage, the data recorded from the Fitbit within the Unity game engine and the Polar data recorded via an iPad application was aligned, achieved in a two-fold stage [8]. Firstly, each data stream provides a timestamp of when the recording started, which was used to align the combined start time. This stage aids data sanitization and the removal of repeat runs, where a participant may have two separate runs recorded through the game but one longer Polar session.

Following, an automatic testing procedure was completed to measure the perceived lag in data trends and alignment. Firstly, both of the participants' files were read from the systems, where one file corresponds to each of the data streams detailed above. 0 Beats Per Minute (BPM) values where the Polar or Fitbit were set up were removed, as these have no bearing on the true heart rate of the participant and could cause an

[7] https://www.polar.com/uk-en/sensors/h10-heart-rate-sensor, Accessed 11/03/2024

[8] https://apps.apple.com/us/app/polar-flow/id717172678, Accessed 06/03/2024

incorrect reduction in the validity of the Fitbit. The Fitbit data was processed to only 1 in 30 data points, as heart rate was recorded at a fixed 30 Frames Per Second (FPS), thus 30 data points per second from Unity were recorded, whereas 1 data point per second was recorded from the Polar heart rate monitor.

A standard signal processing cross-correlation 1 was performed to calculate a discrete correlation between the Unity and Polar data.

$$c_k = \sum_n a_{n+k} \cdot \overline{v}_n \tag{1}$$

$$\tau = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}} \tag{2}$$

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{3}$$

Following, the data was arranged to process the maximum time lag between the Fitbit BPM and the Polar BPM, enabling us to track the trend of heart rate events over the specific BPM given.

The two streams of data were cropped to the same length for further statistical analysis. Three additional analyses were performed:

- *Kendall Tau* Eq 2 [34]: Measures the significance of the rank correlation of two data streams. The metric ranges from 1 for exact similarity, 0 for no similarity and -1 for reverse similarity.
- *Spearman Rho* Eq 3 [35]: Utilises a monotonic function to measure the rank of the data streams. The metric complements the Kendall Tau metric and follows the same scoring techniques.
- *Dynamic Time Warping (DTW)* [36]: Measures the similarity between two sequences. This produces a value between 1 for high similarity and 0 for no similarity. This metric allows for a focus on trends in the data with some impact from the difference in heart rate scale.

To highlight the difference in the device BPM scale, the mean and standard deviation of the BPMs were calculated. As such, we demonstrate Fitbit's ability to track both BPM trends and the overall scale of the BPM.

V. Results

The presented results are split into two main sections: a device analysis where the reliability of the Fitbit against the Polar medical-grade Heart Rate monitor in terms of lag was tested, BPM trends, and BPM Scale between the two devices. Then, a survey analysed that was given to the participants to provide feedback on the Cardiac game.

A. Device analysis

1) Time Lag analysis: Fig 3 highlights the correlation between the trends in BPM activity and Fitbit, where the ideal value is 0, meaning no time difference between the two devices, creating a pyramid shape showing that one device will occasionally detect before the other. Our results present a majority peaking at 0, showing a symmetric detection of BPM trends in both devices. However, it also highlights that Fitbit has experienced a significant delay in its trend detection and Polar in several cases, compared to the natural decline of the early detection. A reason for the significant delay in some cases is that Fitbit requires some start time to sync with the game, plus the 5-second delay that is implemented in the Cardia game [4].

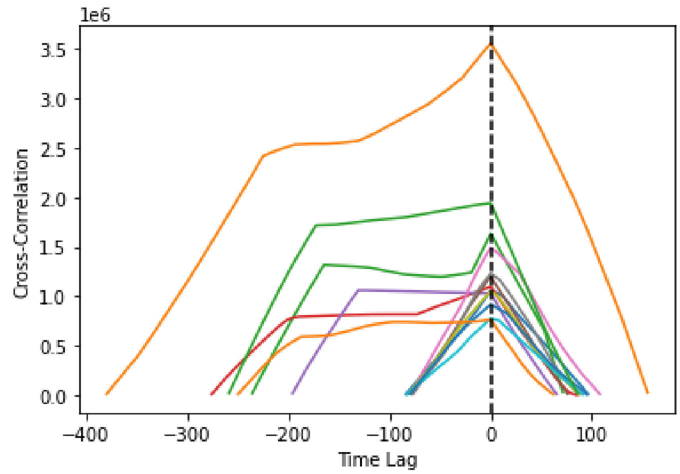

Fig. 3. The time lag between the Fitbit and Polar trends.

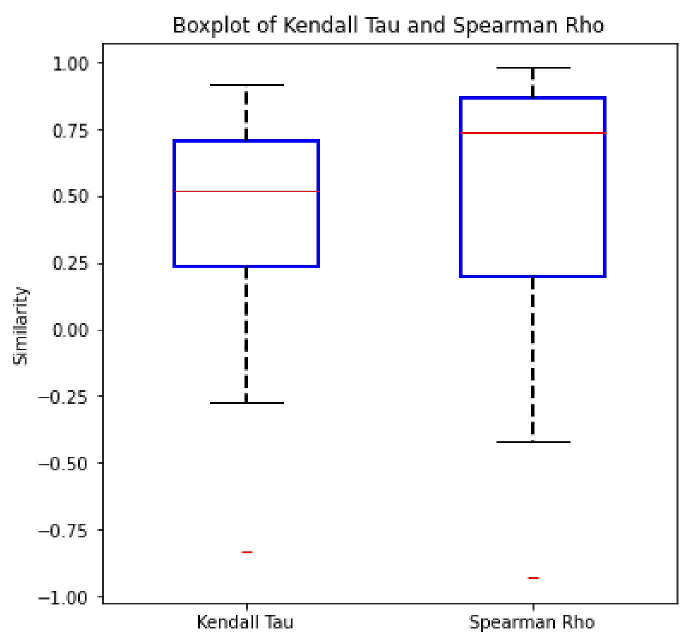

Fig. 4. The Kendal and Spearman analysis scores on the aligned data.

2) Trend analysis: Fig 4 highlights that in both cases, the mean is above 0.5, indicating that in most cases, there is a good similarity between the Unity Fitbit and the Polar data, with the majority of results presenting a 0.2 - 0.8 similarity. However, in some cases, there is either no correlation or an

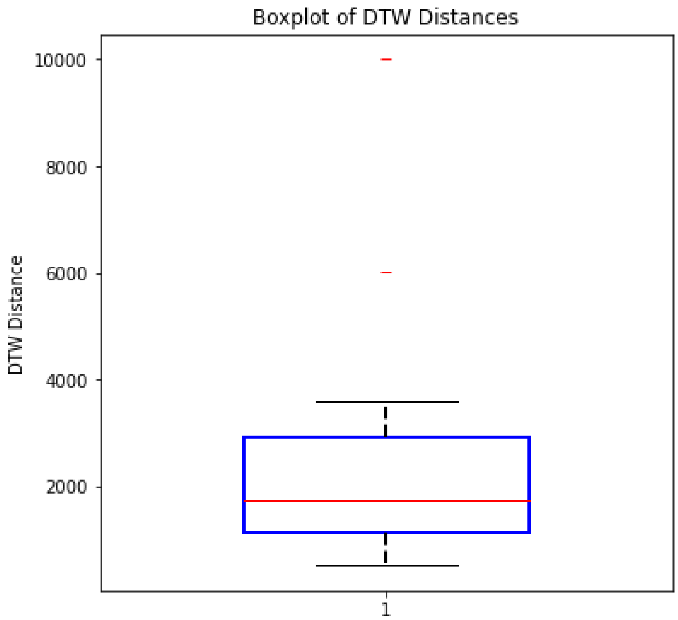

Fig. 5. The score of the DTW analysis on the aligned data.

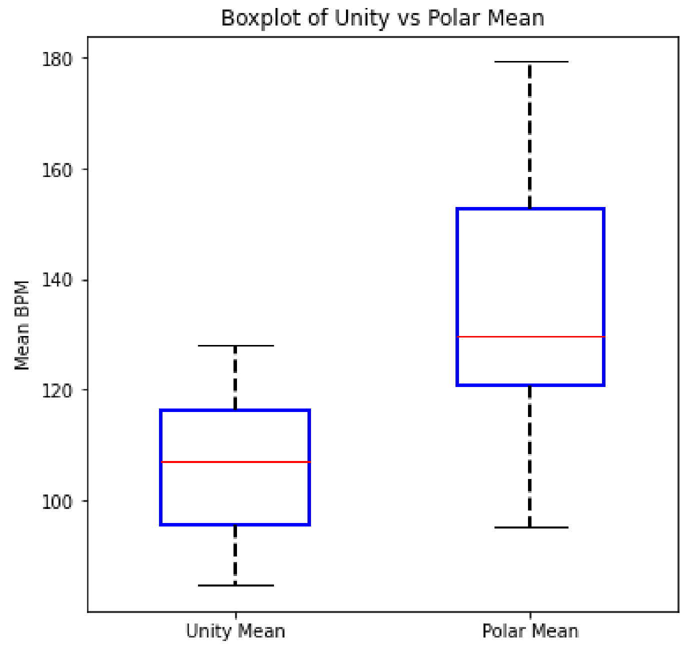

Fig. 6. The mean captured BPM of both Unity Fitbit and the Polar.

inverse similarity, e.g. the data streams had the data trend inverted.

Fig 5 highlights a close similarity in the majority of cases with a compact deviation with a DTW distance that does not exceed 4000. Our results, however, do highlight two cases where a server disconnect between the two streams of data. As the mean DTW distance is below 2000 the majority of the data stream has good similarity between the different devices. Our results highlight that in terms of BPM trends, the two devices are comparable, allowing increases and decreases in BPM to be identified.

3) Scale analysis: As highlighted in Fig 6, Fitbit tends to predict a lower BPM than Polar, with a more concentrated range of values. However, the Polar data demonstrates a mean far beyond the Fitbit's, with only outliers within the Fitbit range. Our data shows, in terms of scale, the Polar is able to track a wider array of BPM range within a normal BPM for individuals performing exercise.

Fig 7, illustrates a similar reaction where the Polar allows for a more dynamic range of BPM activity compared to the Fitbit. This also highlights that Polar is capable of tracking the BPM increase more effectively as the prolonged running commences. Our results determine, in terms of scale, that the two devices are not comparable in a significant way.

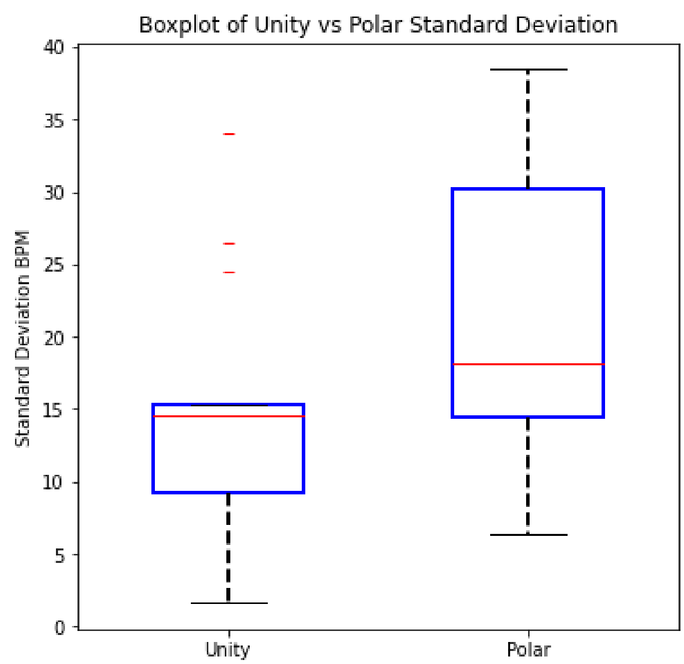

Fig. 7. The Standard deviation of the BPM in both Unity Fitbit and the Polar.

B. Questionnaire analysis

The presented experiments received 14 participants' questionnaires with the answers to 9 questions:

1) Usability, Fun and Adoption (Q1-Q3): Fig 8 shows the Likert scores on three questions with respect to usability (Q1), fun (Q2) and adoption (Q3). It highlights almost all the participants were satisfied with three aspects: usability 11 in 5s and 2 in 4s, fun 5 in 5s and 6 in 4s and adoption 12 in 5s and 2 in 4s. Although no 1s and only 1 in 2s out of the three aspects were noted, more space could be improved on how fun the game was with fewer 5s compared to the other two aspects.

2) Exercise Promotion (Q4-Q5): TimeLMs [37] was used to measure the answers' polarity, a SOTA transformers-based sentiment analysis model trained on around 124M tweets. Fig 9 highlights that the majority agrees the developed game

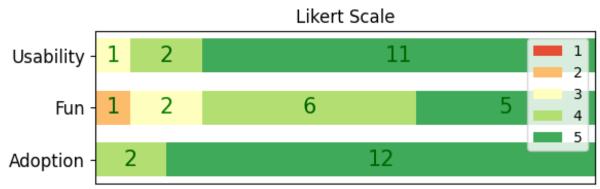

Fig. 8. Bar chart of 14 participants' data on questions that sourced the participant opinion around usability, fun, and adoption. Categories are presented on the Y axis and the number of Likert scores received on the X axis.

is promoting and engaging people to exercise regardless of age. The only negative answer suggests that young kids would be uncomfortable with the game, while the neutral answers suggest similar points.

3) Game Features (Q6-Q7): Fig 10 presents participants' opinions on their experience of two game features. Half of the participants were encouraged to run by a pursuing monster. Several negative and neutral answers stated they did not find the monster immersive or realistic enough to push them forward. Over half of the participants appreciated showing the heart rate. All participants submitted a Yes answer about showing the heart rate during the game. The only answer with negative polarity suggests the game could have an explanation about the heart rate to the players, which is the main trigger of the developed game.

4) Improvements and Free-form Comments (Q8-Q9): A standard English stopwords list was applied to clean the data and KeyBERT [38] was used with Keyphrase Vectorizer [39] to extract the key phrases from the participants' answers. The following generated word clouds are used to visualise the expected improvements and comments from the participants. Fig 11 highlights the interest from the participants in using heart rate in games, and they expect further development and improvements on the monsters, levels and variety (e.g. dancing, different movements). Fig 12, shows that most participants have positive game experiences and give further suggestions on performance, graphics and accessibility considerations.

VI. Discussions

Our paper provides insights into the validity of heart rate measures from an off-the-shelf smartwatch compared with medical grade equipment (RQ1) and the perception of participants on a game experience driven by wearable technology (RQ2). Regarding RQ1, the results in our paper indicate that the Fitbit device is suitable as game input for an exergame, providing the limitations of the technology are considered as part of the game experience. The Fitbit does not have the same ability to track heart rate as medical grade equipment, therefore we do not recommend the use of such technology for clinical-based experiences where heart rate is used towards monitoring patient recovery or other medical insights. A similarity is noted in heart rate trends that does enable the use of off-the-shelf wearables, such as the Fitbit, to track heart rate to a level of accuracy that can be considered for exergames. One potential solution for overcoming the technical limitations

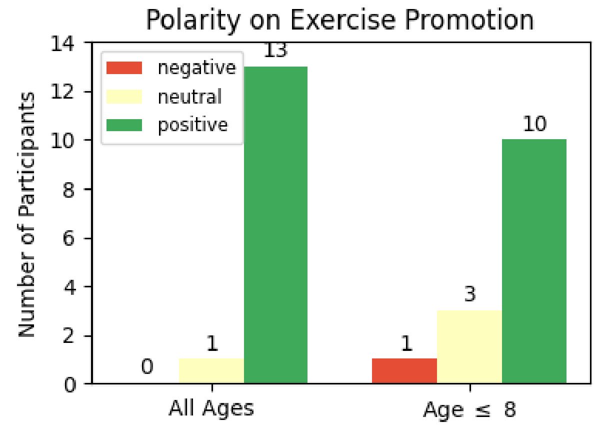

Fig. 9. Bar chart of 14 participants' polarity on questions that sourced the participant opinion on promoting exercises for two age groups. Age groups are presented on the X axis.

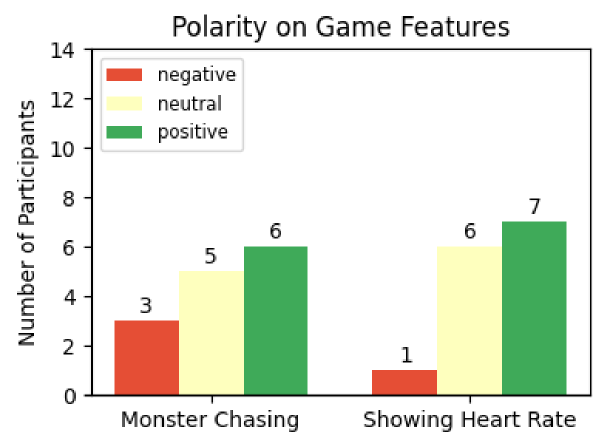

Fig. 10. Bar chart of 14 participants' polarity on questions that sourced the participant opinion on two game features.

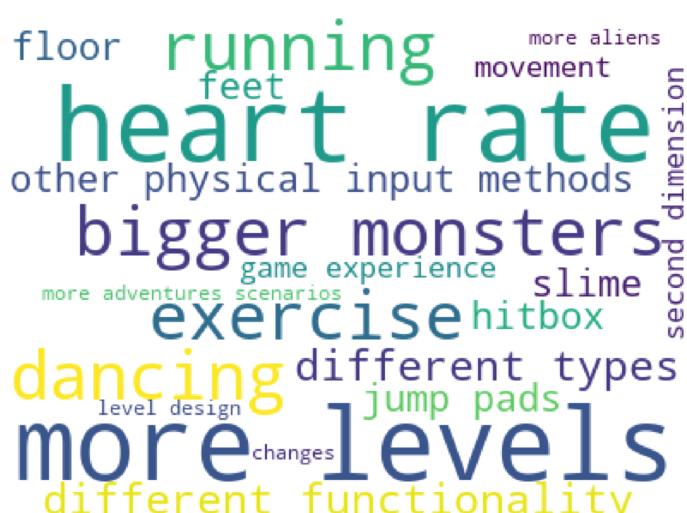

Fig. 11. Word cloud of the free text responses to the question "Are there any changes you would recommend for a future version of the game?".

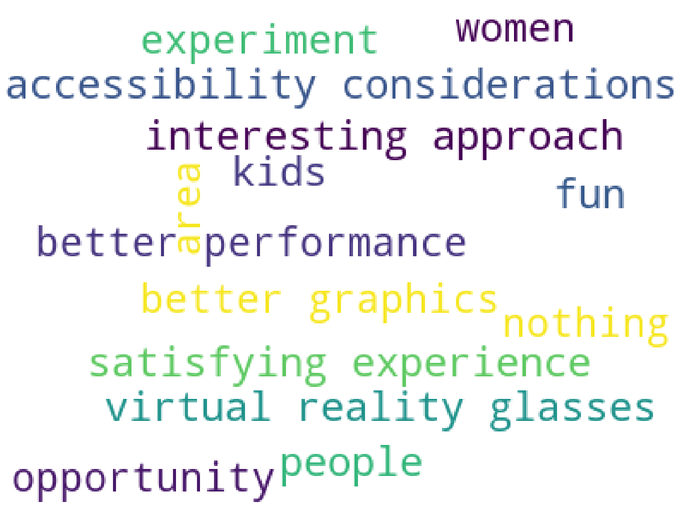

Fig. 12. Word cloud of the free text responses to the question "Please use this space to add any other comments you may wish to add".

of the Fitbit could be sampling the heart rate over a short period of time and using the average of the sample as a ground truth. This will not correct the overall inaccuracy noted in our results, but it can reduce smaller irregularities in individual samples.

Considering RQ2, our results also indicate that the concept of heart rate driven games for exergames is welcomed by adults, encouraging further research in the design and development of such experiences. Participants expressed uncertainty about how well the related exergame could be applied to children, something that should be considered as a future direction of research.

A. Limitations

The limitations are categorised into two groups: technical limitations and procedure limitations. Firstly, the difference in sampling rate between the two devices was a technical limitation. Although the data was processed and mapped to the Polar Data's higher sampling rate of Fitbit, future research may embed Polar HR into the same game experience to remove any issues around incorrect monitoring times and synchronise the sampling rate of the devices. Secondly, the experience does not record the baseline heart rate of each individual, a metric that could provide a clearer insight into the performance of the Fitbit on an individual basis. Furthermore, the study does not compare wearable technology as a whole by sampling several wearables. Our paper focuses on the hardware being used in an existing study but recommend future research consider a broader investigation of a variety of off-the-shelf wearables as game input for exergames.

On procedure limitations, the questionnaires did not source demographic information, an insight that would allow us to investigate the validity across demographic groups. Existing research does highlight bias in the technology [40], and as such, this is a limitation in our understanding of the data. Finally, the sample size *n=14* does limit the statistical significance of our findings, but we will address this limitation by continuing to gather data and publishing and expanded version of our paper in future.

B. Future Work

Future work should continue validating the wearable technology used towards games input, to ensure that the serious goals they set through the game experience are not limited by technological restrictions. We suggest that future research considers defining a methodology for validating wearable devices across a range of game experiences, particularly for healthcare applications.

Our future work will consider how the related technology can be applied towards improving motor skill competency in young children. Further validation will be required to assess the validity of the heart rate readings in young children and how any inaccuracy could be accommodated during game design. Future work will also define a design methodology framework for sensor embedded games, with co-design workshops scheduled for May 2024.

VII. Conclusion

Our paper presents the results of experiments that aimed to identify how valid the measures of an off-the-shelf smartwatch were, compared with medical grade equipment, to test the effectiveness of a Fitbit device as game input, and the results on the adoption of wearable technology as game input. Our empirical results identified that though there is an inconsistency in the reported heart rate between an off-the-shelf wearable device and a medical grade device, there is a similarity in the heart rate trend, allowing off-the-shelf devices to be used as game input, where the heart rate would not be considered as data used towards medical applications. We also discovered that participants welcomed the adoption of wearable technology as game input, as noted by the questionnaire results presented in our Discussions section, particularly when focusing on RQ2, but they highlighted the need for careful consideration and future research before the concept could be applied to children. Our presented insights are limited by the sample size *n=14* and are continuing experiments to increase the sample size and statistical validity of our results.

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