Manuscript accepted for publication in the 47th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2025, Copenhagen, Denmark

An AI-Enabled Low-Cost Wearable to Support Musculoskeletal Rehabilitation: A Proof of Concept

Ivy Mumuni[1], Darren Player[1], Rokhsaneh Tehrany[3], Tom Carlson[1],

***Abstract*— Musculoskeletal (MSK) disorders remain one of the leading causes of disability worldwide. Although multi-modal physiotherapy, an approach that combines manual therapy, exercise therapy and education is the recommended core treatment, many patients continue to face challenges. Adhering to prescribed home exercise programs, staying motivated and performing exercises correctly are amongst the major obstacles faced in the absence of therapist supervision, which can significantly impact treatment outcomes. This pilot study explores the potential to integrate an artificial intelligence (AI)-enabled chatbot with a novel electromyography (EMG) device to enhance engagement and performance as part of MSK rehabilitation. Fifteen healthy adults played two versions of a game, one with the AI chatbot and one without, with the device positioned on the forearm to measure Electromyography (EMG) signals and control the game. The AI-enabled game was associated with a statistically significant increase in muscle activity and game performance. However, no statistically significant differences were identified for engagement based on assessments using the Game Engagement Questionnaire (GEQ). These findings suggest that while AI can increase physical engagement and task execution, further investigation is needed to understand the impact on user engagement. This study lays the groundwork for future research on AI-driven home-based MSK rehabilitation.**

***Clinical relevance*— These preliminary findings inform the development of a program of work that aims to establish the role of AI for supporting engagement with home-based exercises among patients requiring rehabilitation for MSK conditions.**

I. INTRODUCTION

Musculoskeletal (MSK) conditions, affecting the joints, muscles and bones impact nearly one-third of the UK population, with around 20 million people living with an MSK condition, such as arthritis, low back pain and neck pain [1]. These conditions are the largest contributors to Years Lived with Disability (YLDs) in the UK and have a substantial socioeconomic burden, accounting for approximately £5 billion annually in direct NHS costs and lost productivity. In 2022 alone, these conditions were responsible for 23.4 million working days lost, making them the third most common cause for work absence [1].

I.M is supported by a UCL UKRI Center for Doctoral Training in AI-enabled Healthcare studentship (EP/S021612/1).

[1]UCL Aspire Create, University College London, London, WC1E 6BT `ivy.mumuni.23@ucl.ac.uk`

[3]Therapies Department, Royal National Orthopaedic Hospital,Stanmore, HA7 4LP

In recent years, global health priorities have shifted from communicable disease to non-communicable disease, such as osteoarthritis [2]. Managing MSK disorders requires a multidisciplinary approach, involving health care professionals from various specialties, including pharmacological, surgical and Allied Health Professionals (AHPs) such as physiotherapists and occupational therapists [3]. Guidelines from the Osteoarthritis Research Society International (OARSI) recommend a non-surgical management approach, including the provision of home based-rehabilitation involving exercise therapy [4], [5].

Despite its importance, adherence to home-based rehabilitation programs remains a significant challenge for people with MSK conditions due to a multitude of reasons [6], such as low motivation and self-efficacy, in addition to factors like socioeconomic status, mental health and level of family and peer support [7]. Higher adherence rates are more likely achieved during supervised rehabilitation programs, highlighting the importance for enhancing patients' self-efficacy and motivation in the home setting [8]. Low adherence can have negative effects on physical and psychological outcomes leading to worsening symptoms and the need for additional follow-up care.

Artificial Intelligence (AI) provides a promising solution to enhance adherence and engagement with home-based exercise programs delivered as part of MSK rehabilitation. AI-powered solutions can provide personalized, adaptive programs tailored to individual needs, through the provision of real-time feedback. These capabilities have the potential to mimic a similar level of supervision and support as would be achieved with a therapist [9]. Integrating real-time monitoring and feedback while collecting physiological data, enables healthcare professionals to monitor progress remotely. Gamifying exercise therapies can further transform home-based exercises by making repetitive movements more interactive, enjoyable and engaging in order to enhance motivation [10].

Studies have shown that AI-based tools, such as conversational agents and gamification strategies, can enhance user engagement and immersion in various settings. Fraser et al., 2018 [11] demonstrated that emotionally aware conversational agents can improve engagement by maintaining immersion, while Pirovano et al., 2012 [12] highlighted the importance of balancing difficulty adjustments to maintain flow in gaming experiences. However, these benefits also come with challenges, as AI features may inadvertently increase cognitive load or disrupt user flow if not carefully designed [13]. Addressing these challenges in MSK rehabilitation requires robust adaptive algorithms that can process real-time data and ensure personalization for diverse patient needs [14]. While these previous studies have explored emotional AI in the context of spoken conversational agents with Non-Playable Characters (NPCs), they did not influence gameplay mechanics [11] for the users.

Real-time data processing from physiological sensors, such as electromyography (EMG), can be easily influenced by noise and variability, requiring stringent algorithms to ensure accuracy. Additionally, ensuring that AI systems adapt to the wide variability in patient responses is crucial for success. By leveraging insights from studies [15], which have demonstrated the benefits of EMG-based feedback for improving muscle strength, the current study aims to address gaps in rehabilitation gaming.

The aim of this study was to evaluate the feasibility of an AI-enabled muscle-controlled game in improving engagement and performance compared to a non-AI version of the game. Specifically, this study investigates how the addition of an AI-chatbot and real-time feedback influenced player engagement, game metrics and muscle activation (measured via EMG). This work addresses gaps identified in related studies, such as the need for adaptive algorithms in rehabilitation settings [10], [14], and provides insights into the opportunities and challenges of integrating AI into rehabilitation games.

II. Methods and Materials

A. Data

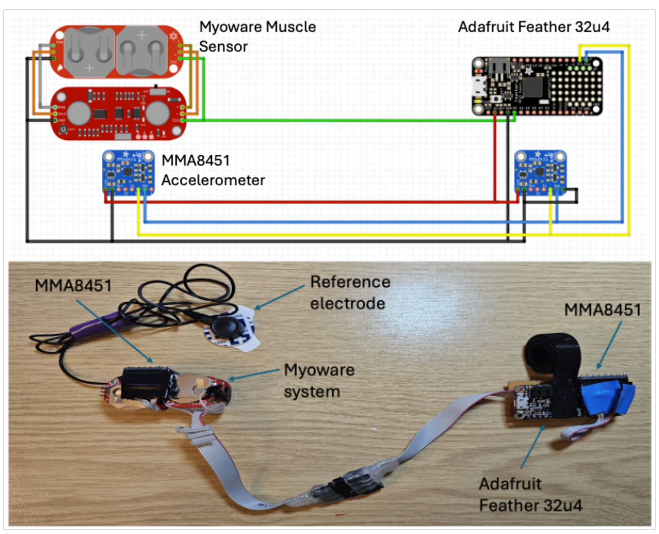

Fig. 1. The schematic illustrates the integration of the MyoWare Muscle Sensor and MMA8451 accelerometers with the Adafruit Feather 32u4 micro-controller. The MyoWare Muscle Sensor (top-left) detects electromyography (EMG) signals, providing data to the Feather via the analog pin (green wire). Two MMA8451 accelerometers (bottom) measure motion data, which was not utilized in this study.

In this study, we evaluated EMG data recorded from fifteen healthy participants (6 female and 9 male), game performance metrics and qualitative data, under ethical approval by the UCL Research Ethics Committee (Study ID: 6860/015). Player engagement was measured using the Games Engagement Questionnaire (GEQ), which is a validated questionnaire [16], comprising of 19 items distributed across four dimensions: absorption, flow, presence and immersion. Participants rated each item against a 5 point Likert scale, immediately after playing both versions of the game in order to measure their initial response capturing perceptions on engagement.

EMG signals were collected via a wearable prototype device which was developed by the research team building upon the early works of Magee et al., 2017 [17]. Fig. 1 displays the circuit diagram of the device, which comprises of a MyoWare EMG sensor, an Adafruit Feather 32u4 Bluefruit microcontroller and two MMA8451 accelerometers (the accelerometers were not used in the scope of this project). The total cost of all prototype components remained under £100, making the device a more cost-effective solution for integrating home-based rehabilitation, in comparison to laboratory-based equipment. The device sensors captured, rectified and filtered EMG signals, which reflect muscle contractions by measuring the amplitude. Higher amplitudes indicate stronger muscle contractions, while lower amplitudes closer to baseline suggest relaxation. The data was sampled at a rate of 100ms to allow analysis of time-based patterns. A study has been undertaken to experimentally validate the feasibility of measuring joint angles with this developed low-cost device compared to an OptiTrack motion tract system, revealing excellent repeatability measurements for static tests and acceptable repeatability for dynamic test [18].

B. Development Process

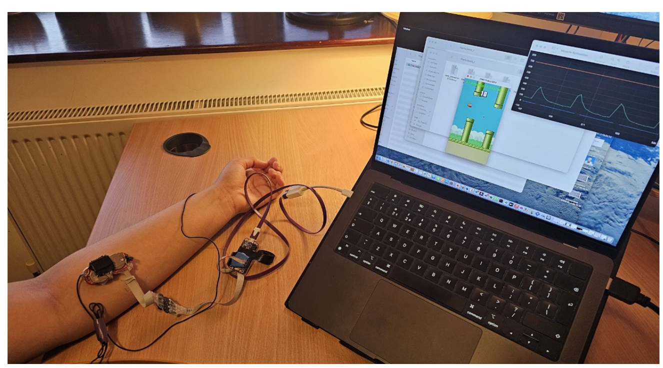

Fig. 2. Experiment set up with participant wearing the device and connected to the computer where the game was played. Along with the EMG activation spikes displayed on screen (top left on computer screen).

An open-source Flappy Bird framework (available on GitHub), originally developed by Sourabh Verma was utilized during this study[1]. Leveraging this existing code-base reduced development time, allowing greater focus on necessary modifications and the integration of the chatbot which was central to the experiment. The first step for integrating

[1]https://github.com/sourabhv/FlapPyBird

the prototype device into the game involved adapting the game play mechanics to respond to muscle signals.

When a contraction occurred, the MyoWare sensor processed the raw EMG data to produce a clean, interpretable EMG signal that reflects muscle activity intensity. This signal typically exhibits an approximate linear relationship with muscle activation levels. This processed signal was sent to the micro-controller, where a spike in the EMG signal was observed (Fig. 2). If the signal exceeded a threshold of 60 units above the baseline, this provided indication of a successful muscle contraction, the Arduino sends an "F" representing a 'flap' command over serial communication. The modified game interprets this signal as a command to make the bird "flap". This setup enabled players to control the game solely through their muscle contractions in order to make the experience more immersive and interactive. While Fig. 2 illustrates the device placed on the forearm of the participant, it is designed for uses on other parts of the body such as the knee. Future studies will explore the application of this wearable device, AI and gamification in these alternative placements.

Game constraints were determined based on prior research on similar games and piloting sessions. The game aligns with principles of adaptive difficulty commonly used in game design, where the game adjusts to the player's skill level to maintain a state of "flow," a concept introduced by Csikszentmihalyi [19]. Both versions of the game started with the same difficulty level and default parameters. In the non-AI-enabled game, the player could not make choices about game-play instead, the game was pre-programmed to adjust based on score.

In the AI-enabled game, the player could interact with a chatbot to adjust the game's difficulty level based on their preferences and performance. The chatbot, created using Rasa, provided real-time feedback and interactions aimed at increasing engagement and personalizing the experience. Rasa is an open-source machine learning framework for building contextual assistants capable of handling actionable tasks [20]. The framework architecture consists of two main components: Rasa Core, which manages the dialogue flow and Rasa NLU (Natural Language Understanding), which processes player input to extract relevant information. Rasa NLU employs the Dual Intent and Entity Transformer (DIET) architecture for intent classification and entity extraction [21].

In the chatbot-enabled game, custom actions were designed to interact with the game's back-end, retrieving and adjusting game parameters such as pipe gap, speed and flap strength. By leveraging Flask routes, the custom actions dynamically accessed the current state of these parameters and modified them based on player input, such as perceived difficulty or achieved points. This dynamic adjustment enabled real-time responsiveness to player preferences, creating a personalized and engaging gaming experience where difficulty levels could be fine-tuned through natural language interactions with the chatbot. These interactions were text based and took place during gameplay when specific parameters had been reached e.g 20 points, allowing the user to communicate their preferences such as increasing the speed of the game. Fig. 3 illustrates an example text based conversation with the chatbot. The chatbot then interpreted the users input and adjusted the game parameters as described above. In the non-AI version the difficulty adjustments were pre-programmed and linear.

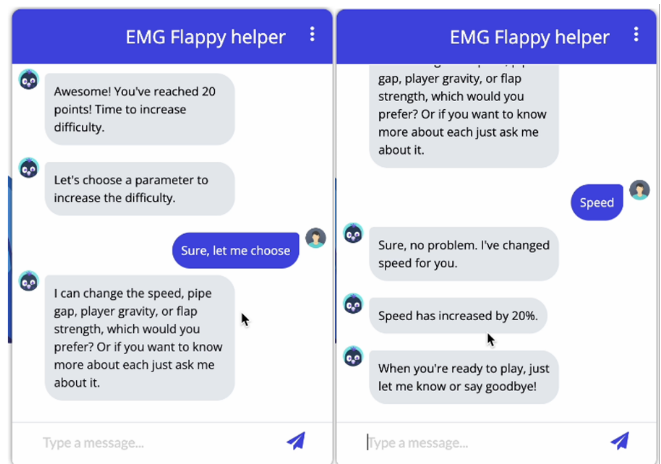

Fig. 3. Example of conversation flow with chatbot in the AI-enabled game

C. Study Design

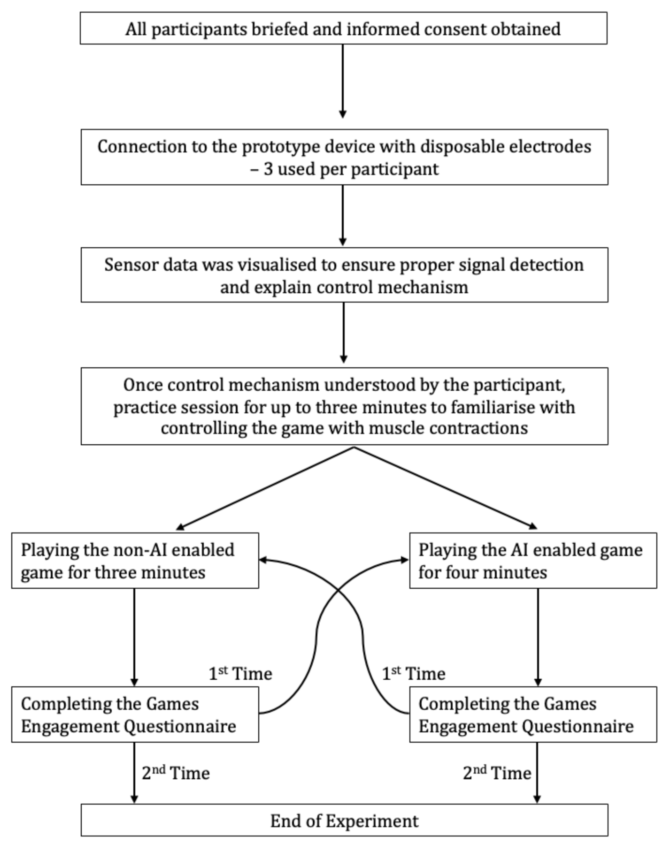

Fig. 4. Experimental protocol flow diagram.

To control for potential order effects and ensure validity, a counterbalanced design was employed [22]. Each participant played both versions of the game: one with AI features and one without. A systematic approach was used to vary the sequence in which participants experienced the two game versions, ensuring that order effects were evenly distributed across conditions. This design aimed to reduce variability due to individual differences and learning effects, to detect differences in engagement between the two game versions. Figure 4 presents the experimental protocol flow diagram for this study.

D. Data Analysis

To determine if there were any differences between games, a series of one-tailed paired t-tests were conducted. This statistical approach was chosen to test specific hypotheses about the game metrics, with different directions of comparison based on expected outcomes, the number of crashes and successful muscle contractions were tested in the "less than" direction, while the total score was tested in the "greater than" direction.

To account for possible type 1 errors arising from multiple comparisons, Bonferroni corrections were applied, adjusting the alpha level to 0.0167 (α) to maintain the overall significance level across all tests. While the correction is a conservative method, it was deemed appropriate given the small sample size (n=15).

The raw EMG data collected during game-play underwent a comprehensive normalization process to ensure consistency across participants and conditions. This pre-processing step was crucial to minimize variability due to individual differences in muscle activity, electrode placement and muscle strength. A normalization factor was computed for each participant by averaging their top five valid EMG values during game-play, which served as a reference for peak muscle activity. All EMG values were then scaled to this normalization factor, converting the raw signal into a percentage of peak muscle contraction. While this method did not use a formal Maximum Voluntary Isometric Contraction (MVIC) test for calibration, it ensured session-specific normalization tailored to each participant. This normalization process was applied uniformly across both AI and non-AI conditions to ensure that differences were attributable to game-play rather than individual variability. Due to the non-normal distribution of the EMG data, a Wilcoxon Signed-Rank test was performed for this dataset.

III. Results

A. EMG data

Muscle activation was assessed by comparing EMG data across the minutes of game-play. By segmenting the data into one-minute intervals, trends were more apparent. The median EMG values indicated that the AI game version generally resulted in slightly higher muscle activation compared to the non-AI version. Notably, during the third minute of game-play, the AI condition showed the highest median value of 0.16, while the non-AI condition recorded 0.11. The results from the Wilcoxon Signed-Rank test indicated a statistically significant increase in muscle activation for the AI condition compared to the non-AI condition ($p < 0.05$). The AI-enabled version required players to engage with the chatbot as part of the gameplay, which naturally extended the overall playtime compared to the uninterrupted and continuous non-AI version. To maintain similarity and fairness between the game versions the AI game was allocated a longer duration.

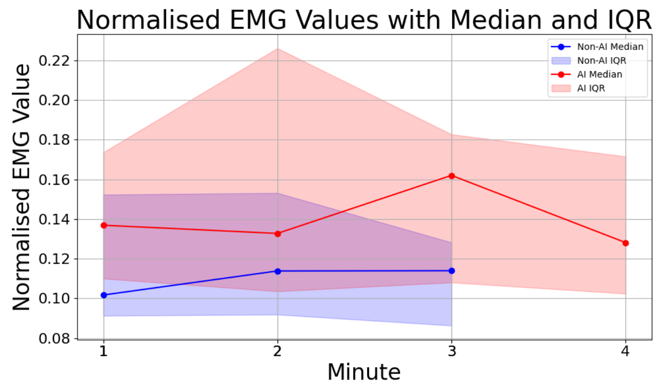

Fig. 5. Normalized EMG values over time for both AI and Non-AI conditions, segmented by one-minute intervals with the inter-quartile range.

B. Game Metrics

Three metrics were analyzed: total score, number of crashes and number successful muscle contractions. The mean number of successful muscle contractions during the AI-enabled game was $86.87{\pm}24.58SD$, compared to $118.13{\pm}23.44SD$ in the non-AI enabled game. The paired t-test revealed a statistically significant decrease in the number of contractions in the AI condition ($p < \alpha$).The paired t-test showed the number of crashes was also significantly lower in the AI-enabled game $(12.07 \pm 3.15SD)$ when compared with the non-AI enabled game $(15.60 \pm 4.74SD)$. The total score had a mean value of $24.60{\pm}24.46SD$ in the AI-enabled game compared with $42.07{\pm}29.82SD$ in the non-AI enabled game. The paired t-test indicated the difference between the two conditions was not statistically significant ($p > \alpha$).

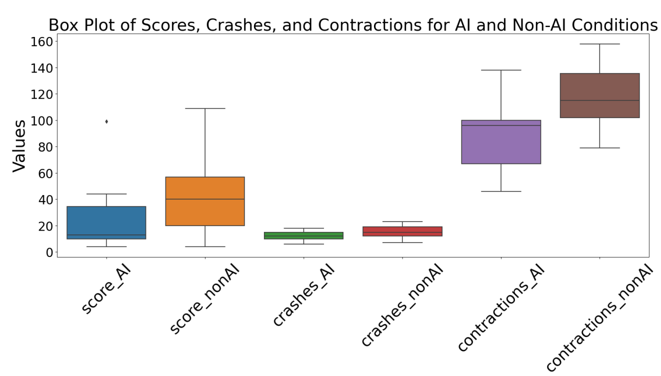

Fig. 6. Box plot for both game versions showing game metrics.

C. Games Engagement Questionnaire

The mean absorption score was slightly higher for the non-AI enabled game ($2.45 \pm 1.10SD$), compared to the AI enabled game, at $2.39 \pm 1.11SD$. Flow had almost identical mean scores with $2.94 \pm 1.19SD$ for the non-AI enabled game compared to $2.93 \pm 1.24SD$. Presence dimension showed a mean score of $3.18 \pm 1.17SD$ for the non-AI enabled game and $3.08 \pm 1.24SD$ for the AI-enabled game. Lastly, immersion had the highest mean scores with the non-AI game scoring $4.27 \pm 0.59SD$ and the AI-enabled game mean of $4.20 \pm 0.68SD$. A paired t-test indicated no statistically significant differences in any tested dimension between game versions ($p > 0.05$).

In addition to the questionnaire data, users had an option to leave comments about the game which can be seen in Table I.

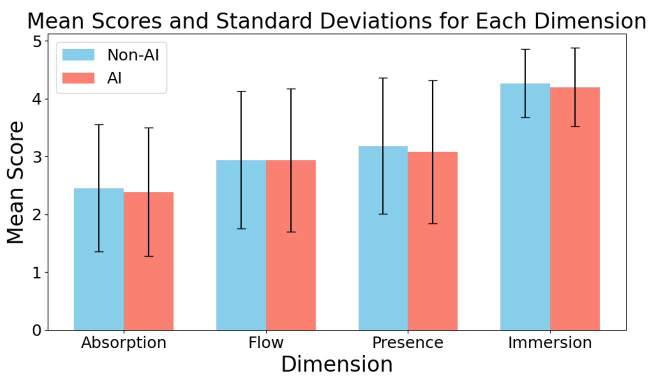

Fig. 7. GEQ mean scores for all dimensions.

TABLE I
COMMENTS FROM PARTICIPANTS PER GAME VERSION

AI-enabled game	**Non-AI enabled game**
"More encouragement with the bot, makes me want to achieve a higher score"	"This game is really fun, and the controller is unique!"
"The chatbot is interesting and I like the stats at the end, the voice is motivational to play more"	"It was addictive and harder than I thought to control it with my muscle for me"
"I thought this game is interesting"	"The game makes you want to continue playing it as you want to improve"
"The game works really well however I hate flappy bird"	

IV. DISCUSSION

This study explored the feasibility and impact of AI-enabled features on player engagement, game performance and muscle activation within a rehabilitation gaming context on healthy participants. Data obtained from EMG signals demonstrated there was a significant increase in muscle activation associated with the AI-enabled game, when compared to the non-AI enabled game. Although these preliminary findings should be interpreted with caution in light of the small sample size, these observations suggest that the AI features provided a more dynamic experience to facilitate active muscle engagement. These findings align with previous research by Lyons et al., 2003 [15], which showed that EMG-based feedback in gaming environments can improve muscle strength compared to controls. The increase activation observed here indicates the AI-enabled games' potential for therapeutic applications, especially in rehabilitation where maintaining or increasing muscle activation is usually a key goal.

Although it was hypothesized that the AI-enabled game would be associated with improved player engagement, no differences were identified between the groups. Although the sample size was not sufficiently powered, these findings may also reflect challenges associated in capturing subtle differences of player experiences through standardized questionnaires. Similar findings have been reported in prior studies, where engagement metrics showed limited sensitivity to subtle variations in game design [14].

Qualitative feedback from participants, however highlighted the motivational role of the AI-chatbot, suggesting that the chatbot may have positively influenced engagement in ways not fully captured by the GEQ. For instance, participants noted that the chatbot provided encouragement and increased their motivation to continue playing. This is consistent with Fraser et al., 2018 [11], who found that emotionally aware spoken conversational agents enhanced user engagement by maintaining immersion. Future studies should consider using mixed-method approaches, incorporating tools like the Intrinsic Motivation Inventory (IMI) [23] and semi-structured interviews to in order to obtained a more detailed understanding of its impact. In light of this feedback, offering a variety of games that utilize the same physical actions but cater to different players preferences could further enhance the engagement and overall experience, as can be seen by the final comment.

It is also worth considering that participants may have already been maximally engaged, leaving little room for improvement in engagement metrics. The game duration (3-4 mins) may not have been sufficient to fully test these parameters, as longer play sessions might reveal more pronounced effects on engagement. The small sample size in this study (n=15) could have led to underpowered statistics, limiting the ability to detect subtle differences. Future studies with larger sample sizes are needed to fully assess the impact of AI features on player engagement.

Game metrics revealed interesting exchanges between performance and AI features. While the AI-enabled game significantly reduced the number of crashes, suggesting improved precision and focus, it did not result in higher total scores compared to the non-AI game. These findings suggest that the chatbot and AI features, while beneficial for precision, may have inadvertently introduced distractions or increased cognitive load. While EMG data indicated increased muscle activation in the AI-enabled condition, this was also accompanied by a decrease in the number of muscle contractions and lower total score. One possible interpretation of these results could be the participants may have exerted more effort but with less precise game control, or alternatively the participants had fewer but more controlled contractions where participants were more measured and rhythmic in their efforts. Similar challenges have been noted in studies where AI features disrupted user flow [13] or led to overestimation of player abilities when difficulty adjustments were user-controlled [12]. Moreover, allowing participants to adjust game parameters in the AI condition may have resulted in overly difficult settings, further hindering performance. Addressing these challenges requires careful consideration of how AI features interact with game-play elements and player cognition. Analyzing the chatbot interactions could provide insight on the influence on player behavior and should also be considered. This reduction in crashes supports the idea that the AI may have enhanced the player's ability to navigate the game more effectively, or alternatively the game may have been made easier or become better tailored to the players current ability.

V. Conclusion

Despite the challenges, these findings demonstrate the potential of AI to enhance rehabilitation gaming when designed effectively. Future work should focus on refining AI features to balance engagement, cognitive load, and performance. Larger participant samples are necessary to improve statistical power, and adaptive algorithms, such as reinforcement learning could dynamically adjust game difficulty based on real-time feedback, including %MVIC calibration. Extending game durations may also provide more opportunities to observe engagement and performance differences. Integrating advanced AI techniques, such as emotionally aware conversational agents or generative adversarial networks (GANs), could further enhance personalization and adaptability [24]. This study provides a foundation for exploring dynamic, adaptive systems that balance engagement with therapeutic goals, paving the way for innovative rehabilitation technologies.

Acknowledgment

I.M would like to thank all participants in this study for their support in carrying out this work.

References

[1] Versus Arthritis, "va_state-of-msk-report-nov2024-1," tech. rep., Versus Artritis, Nov. 2024.

[2] A. T. Nguyen, I. M. Aris, B. D. Snyder, M. B. Harris, J. D. Kang, M. Murray, E. K. Rodriguez, and A. Nazarian, "Musculoskeletal health: an ecological study assessing disease burden and research funding," *The Lancet Regional Health - Americas*, vol. 29, p. 100661, Jan. 2024.

[3] N. J. Collins, H. F. Hart, and K. a. G. Mills, "Osteoarthritis year in review 2018: rehabilitation and outcomes," *Osteoarthritis and Cartilage*, vol. 27, pp. 378–391, Mar. 2019.

[4] A. Cieza, K. Causey, K. Kamenov, S. W. Hanson, S. Chatterji, and T. Vos, "Global estimates of the need for rehabilitation based on the Global Burden of Disease study 2019: a systematic analysis for the Global Burden of Disease Study 2019," *The Lancet*, vol. 396, pp. 2006–2017, Dec. 2020. Publisher: Elsevier.

[5] T. E. McAlindon, R. R. Bannuru, M. C. Sullivan, N. K. Arden, F. Berenbaum, S. M. Bierma-Zeinstra, G. A. Hawker, Y. Henrotin, D. J. Hunter, H. Kawaguchi, K. Kwoh, S. Lohmander, F. Rannou, E. M. Roos, and M. Underwood, "OARSI guidelines for the non-surgical management of knee osteoarthritis," *Osteoarthritis and Cartilage*, vol. 22, pp. 363–388, Mar. 2014.

[6] S. Bassett, "The assessment of patient adherence to physiotherapy rehabilitation," *New Zealand Journal of Physiotherapy*, vol. 31, pp. 60–66, Jan. 2003.

[7] K. Jack, S. M. McLean, J. K. Moffett, and E. Gardiner, "Barriers to treatment adherence in physiotherapy outpatient clinics: a systematic review," *Manual Therapy*, vol. 15, pp. 220–228, June 2010.

[8] A. M. A. Picorelli, L. S. M. Pereira, D. S. Pereira, D. Felício, and C. Sherrington, "Adherence to exercise programs for older people is influenced by program characteristics and personal factors: a systematic review," *Journal of Physiotherapy*, vol. 60, pp. 151–156, Sept. 2014.

[9] V. C. Kaelin, M. Valizadeh, Z. Salgado, N. Parde, and M. A. Khetani, "Artificial Intelligence in Rehabilitation Targeting the Participation of Children and Youth With Disabilities: Scoping Review," *Journal of Medical Internet Research*, vol. 23, p. e25745, Nov. 2021.

[10] H.-T. Jung, T. Park, N. MAhyar, S. Park, T. Ryu, Y. Kim, and S. I. Lee, "Rehabilitation Games in Real-World Clinical Settings: Practices, Challenges, and Opportunities," *ACM Trans. Comput.-Hum. Interact.*, vol. 27, pp. 41:1–41:43, Nov. 2020.

[11] J. Fraser, I. Papaioannou, and O. Lemon, "Spoken Conversational AI in Video Games: Emotional Dialogue Management Increases User Engagement," in *Proceedings of the 18th International Conference on Intelligent Virtual Agents*, IVA '18, (New York, NY, USA), pp. 179–184, Association for Computing Machinery, Nov. 2018.

[12] M. Pirovano, R. Mainetti, G. Baud-Bovy, P. L. Lanzi, and N. A. Borghese, "Self-adaptive games for rehabilitation at home," in *2012 IEEE Conference on Computational Intelligence and Games (CIG)*, pp. 179–186, Sept. 2012. ISSN: 2325-4289.

[13] K. Sharma, K. Mangaroska, N. van Berkel, M. Giannakos, and V. Kostakos, "Information flow and cognition affect each other: Evidence from digital learning," *International Journal of Human-Computer Studies*, vol. 146, Nov. 2020.

[14] T. Schachner, R. Keller, and F. V Wangenheim, "Artificial Intelligence-Based Conversational Agents for Chronic Conditions: Systematic Literature Review," *Journal of Medical Internet Research*, vol. 22, p. e20701, Sept. 2020.

[15] G. Lyons, P. Sharma, M. Baker, S. O'Malley, and A. Shanahan, "A computer game-based EMG biofeedback system for muscle rehabilitation," in *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE Cat. No.03CH37439)*, vol. 2, pp. 1625–1628 Vol.2, Sept. 2003. ISSN: 1094-687X.

[16] J. H. Brockmyer, C. M. Fox, K. A. Curtiss, E. McBroom, K. M. Burkhart, and J. N. Pidruzny, "The development of the Game Engagement Questionnaire: A measure of engagement in video game-playing," *Journal of Experimental Social Psychology*, vol. 45, pp. 624–634, July 2009.

[17] E. Magee, S. Ourselin, D. Nikitichev, T. Vercauteren, and A. Vanhoestenberghe, "The Bionic Clicker Mark I & II," *Journal of Visualized Experiments*, Aug. 2017.

[18] Liu , Zekun, "Validation of a low-cost wearable EMG prototype device to support knee extension exercises," in *2025 47th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, 2025.

[19] M. Csikszentmihalyi, *Flow: The Psychology of Optimal Experience*. Harper & Row, 1990.

[20] T. Bocklisch, J. Faulkner, N. Pawlowski, and A. Nichol, "Rasa: Open Source Language Understanding and Dialogue Management," Dec. 2017. arXiv:1712.05181.

[21] T. Bunk, D. Varshneya, V. Vlasov, and A. Nichol, "DIET: Lightweight Language Understanding for Dialogue Systems," May 2020. arXiv:2004.09936.

[22] P. S. Jensen, H. K. Watanabe, and J. E. Richters, "Who's Up First? Testing for Order Effects in Structured Interviews Using a Counterbalanced Experimental Design," *Journal of Abnormal Child Psychology*, vol. 27, pp. 439–445, Dec. 1999.

[23] E. Y. Leng, W. Z. b. W. Ali, R. Baki, and R. Mahmud, "Stability of the Intrinsic Motivation Inventory (IMI) For the Use of Malaysian Form One Students in ICT Literacy Class," *Eurasia Journal of Mathematics,*

Science and Technology Education, vol. 6, pp. 215–226, Dec. 2010. Publisher: Modestum.

[24] J. Albert, P. Glöckner, B. Pfitzner, and B. Arnrich, "Data Augmentation of Kinematic Time-Series From Rehabilitation Exercises Using GANs," in *2021 IEEE International Conference on Omni-Layer Intelligent Systems (COINS)*, pp. 1–6, Aug. 2021.