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Original Article

Ability-Based Balancing Using the Gross Motor Function Measure in Exergaming for Youth with Cerebral Palsy

Alexander MacIntosh, MSc,[1] Lauren Switzer, MSc,[1] Susan Hwang, BSc,[2]
Adrian L. Jessup Schneider, MSc,[2] Daniel Clarke, BSc,[2]
T.C. Nicholas Graham, Dr-Ing,[2] and Darcy L. Fehlings, MD[1,3]

Abstract

Objective: To test if the gross motor function measure (GMFM) could be used to improve game balancing allowing youth with cerebral palsy (CP) with different physical abilities to play a cycling-based exercise videogame together. Our secondary objective determined if exergaming with the GMFM Ability-Based algorithm was enjoyable.
Materials and Methods: Eight youth with CP, 8–14 years of age, GMFM scores between 25.2% and 87.4% (evenly distributed between Gross Motor Function Classification System levels II and III), competed against each other in head-to-head races, totaling 28 unique race dyads. Dyads raced three times, each with a different method of minimizing the distance between participants (three balancing algorithms). This was a prospective repeated measures intervention trial with randomized and blinded algorithm assignment. The GMFM Ability-Based algorithm was developed using a least squares linear regression between the players' GMFM score and cycling cadence. Our primary outcome was dyad spread or average distance between players. The GMFM Ability-based algorithm was compared with a control algorithm (No-Balancing), and an idealized algorithm (one-speed-for-all [OSFA]). After each race, participants were asked ''Was that game fun?'' and ''Was that game fair?'' using a five-point Likert scale.
Results: Participants pedaled quickly enough to elevate their heart rate to an average of 120 ± 8 beats per minute while playing. Dyad spread was lower when using GMFM Ability-Based balancing (4.6 ± 4.2) compared with No-Balancing (11.9 ± 6.8) ($P < 0.001$). When using OSFA balancing, dyad spread was (1.6 ± 0.9), lower than both GMFM Ability-Based ($P = 0.006$) and No-Balancing ($P < 0.001$). Cycling cadence positively correlated to GMFM, equal to 0.58 (GMFM) +33.29 ($R^2_{adj} = 0.662$, $P = 0.004$). Participants rated the games a median score 4/5 for both questions: ''was that game fun?'' and ''was that game fair?.''
Conclusion: The GMFM Ability-Based balancing decreased dyad spread while requiring participants to pedal quickly, facilitating interaction and physical activity.

Keywords: Exergames, Fitness, Game therapy, Youth fitness, Game mechanisms

Introduction

The characteristic decline in function, mobility, and cardiovascular fitness in youth with cerebral palsy (CP) experience as they age leads to less participation in physical activity.[1] Exercise videogames (exergames) can help engage youth in physical activity and provide health benefits, including improvement in cardiovascular fitness[2,3] and decreased sedentary screen time.[4] We have developed a cycling-based exergame called Liberi.[5] The game uses customized recumbent bicycles, designed for youth with CP at Gross Motor Function Classification System (GMFCS) levels II–III,[5] connected through an online multiplayer virtual game world. Participants cycle to move their avatars in the virtual

[1]Bloorview Research Institute, Holland Bloorview Kids Rehabilitation Hospital, Toronto, Canada.
[2]School of Computing, Queen's University, Kingston, Canada.
[3]Department of Pediatrics, University of Toronto, Toronto, Canada.

world. With these exergames, we have observed sustained increases in heart rate indicative of moderate intensity cardiovascular exercise.[2,6] However, there is variability in gross motor function across the spectrum of CP.[7] Children at GMFCS level III use mobility aids such as a walker, whereas children at level II are higher functioning and generally walk unassisted.[7] Even within one GMFCS level, there are great differences in gross motor ability. These differences can impact participation in multiplayer exergames.

In previous studies, a number of methods have been used to allow people to play together (balancing algorithms).[6,8] In the ''One-Speed-for-All'' (OSFA) algorithm, all avatars move at the same speed, provided the player is pedaling. OSFA represents ideal balancing for game success since everyone moves at the same rate. However, there is no explicit motivation to pedal quickly and drive cardiovascular exercise. In the ''No-Balancing'' algorithm, the players' pedaling cadence directly determines the speed of the avatar. The faster a player pedals the faster their avatar goes. While this promotes cardiovascular exercise, it does not balance for differences in gross motor ability. In an unbalanced cycling-based exergame, as is the case with No-Balancing, when one player pedals faster than the others, their avatar will move more quickly, leading to large differences in game success and less interaction between players. Unbalanced exergames can discourage participants who are physically unable to keep pace. Balancing methods in exergames should therefore aim to minimize the distance between players (player spread), regardless of how fast everyone can pedal. At the same time, the balancing method should motivate participants to pedal as quickly as they are able, to promote cardiovascular exercise.

Physiological measures such as heart rate have been proposed to moderate game performance. For instance, Stach et al. moderated game performance using the participant's ability to stay in a target heart rate zone.[9] We have also used target heart rate zones to balance game performance for youth with CP. However, we found that it is more difficult for youth with CP at GMFCS level III to maintain higher heart rates and pedaling cadences than those at level II, making it more difficult for them to reach in-game goals that facilitate game performance.[8] This gap is potentially due to lower muscle endurance of participants at GMFCS level III; therefore, to provide a more equal opportunity for game performance, the exergame balancing method should address different qualities of ability, including strength, endurance, and coordination while accounting for a range of physical abilities.

The gross motor function measure (GMFM-66) may help balance exergames for youth with CP. The GMFM-66 is a Rasch-derived scale that addresses different qualities of ability, including walking, running, and jumping. This metric accurately and validly determines the gross motor functioning of individuals with CP across all GMFCS levels.[10] The scores are normalized and range from 0% to 100%. GMFM scores for children at GMFCS level II–III can vary widely, but are typically between 45% and 90%, with a higher score indicating better gross motor functioning.[11] The GMFM is readily available for many youth with CP. Using GMFM scores to address individual physical abilities in the exergame's balancing algorithms may facilitate cardiovascular exercise by allowing players of different abilities to be competitive. To this end, we have developed a ''GMFM Ability-Based'' balancing algorithm, which uses the GMFM score to minimize the distance between players' avatars. A key feature of the GMFM Ability-Based algorithm is the use of GMFM scores to set a ''threshold cadence'' unique to each participant. At the ''threshold cadence,'' avatars move at maximum speed. Individuals with a higher GMFM score must pedal faster for their avatar to reach maximum speed. Unlike the ''No-Balancing'' algorithm, the GMFM Ability-Based algorithm addresses differences in physical ability by setting a unique threshold cadence for each player to balance game performance while motivating cardiovascular exercise.

The primary objective of this study was to test if the GMFM Ability-Based balancing algorithm could minimize player spread during a cycling-based videogame race. Player spread is the average vertical distance between the two players in a race. We consider low spread to be an indication that the game was balanced. Lower spread would provide opportunities for success between people with CP who have varying gross motor abilities. For reference, GMFM Ability-Based balancing was compared with the ideal balancing condition, the OSFA algorithm, and the No-balancing condition. We hypothesized that the lowest spread between participants would be found with the OSFA algorithm, followed by the GMFM Ability-Based algorithm, and that the No-Balancing algorithm would yield the greatest difference. Our secondary objective was to identify if there were any differences in perceived enjoyment and fairness when using the GMFM Ability-Based algorithm.

Materials and Methods

Participants

Participants were a voluntary convenience sample of eight youth with CP enrolled in a 2-week gross motor camp. Inclusion criteria were: 8–14 years of age, GMFCS level II or III, and the ability to operate a hand-held videogame controller. Exclusion criteria were: orthopedic surgery within 3 months of the study, exercise-induced asthma, heart conditions, and uncontrolled seizures. Ethics approval was granted by the Holland Bloorview and Queen's University Research Ethics Boards. All participants, and a parent/legal guardian for each participant, gave written informed consent.

Study design

This was a prospective repeated measures intervention trial with randomized and blinded algorithm assignment. On each of the 10 days, participants played the exergames for 40 minutes, including 10 minutes of warm-up and cool-down time. The first 4 days were used as ''calibration sessions'', where each participant's threshold cadence for the GMFM Ability-Based algorithm was calculated using their GMFM score. The final 6 days were ''intervention sessions''. During intervention sessions, each participant competed against every other participant, totaling 28 unique race-dyads. Dyads raced three consecutive times with each of the three algorithms. Participants and researchers were blind to the randomly assigned algorithm order.

GMFM ability-based calibration sessions

In the first four sessions, each participant's unique threshold cadence was determined for the GMFM Ability-Based balancing algorithm. During these four sessions, the average cadence each player achieved during an intense 30 second pedaling race was calculated. A least squares linear regression analysis between the players' GMFM scores and average cadence was used to estimate threshold cadence for the following day. For the first day, threshold cadences were estimated based on the average cadence and GMFM scores from a previous study involving 10 participants between GMFCS levels II and III.[8] Each day, the threshold cadences and coefficient of determination were compared with the previous day. To ensure that the threshold cadences appropriately represented participant abilities, each player's average cadence across the four calibration sessions were used in the least squares linear regression (Eq. [1]).

$$Threshold\ Codence = m(GMFM\ score) + b, \qquad (1)$$

where m is the linear scaling factor of the GMFM score and b is the threshold cadence offset across all participants after the calibration sessions. For the exergaming intervention sessions, each player's threshold cadence was calculated given their GMFM score, and the m and b values determined at the end of the calibration sessions that is common to all participants.

Exergaming intervention sessions

Exergaming intervention sessions were completed in two groups of four. Participants rotated between groups, ensuring all dyads raced against each other. Participants raced using each of the three algorithms separated by a rest period of at least 2 minutes. Heart rate was recorded using Polar H1 chest-mounted sensors (Polar Electro, Oulu, Finland). Cadence and distance between avatars were recorded continuously through the custom game software. A detailed description of the exergame station and games have been provided previously.[12] For this study, one of the six mini games (''Gekku Race'') was used to control for differences in game style. Briefly, Gekku Race is a competitive racing game where two participants pedaled to be the first to reach the top of a wall in 30–60 second races to win the race. Avatars moved when the participants cycled and avatar speed was moderated by the balancing algorithm. To isolate gross motor balancing and minimize the effect of fine motor abilities, controller functions were removed for this study.

Outcome measures

Our primary outcome was the distance between players during the head-to-head races (dyad spread). Dyad spread, measured in game distance units, was compared with the three algorithms. The dyad spread was calculated as the average vertical distance between participants' avatars. The average distance during the first 30 seconds in each race was used. Thirty seconds was the length of the shortest race, therefore, allowing for comparison across all trials. Lower spread indicates a closer, more balanced game.

The secondary outcome addressed participants' perceptions when racing with each algorithm. After each race, participants were asked ''Was that game fun?'' and ''Was that game fair?'' Participants indicated responses using a five-point Likert scale with faces and written response ranging from strongly disagree (1) to strongly agree (5). Participants' heart rates were recorded and averaged across the six exergaming intervention sessions. Heart rate was not compared between balancing algorithms as all three algorithms were used during the same session. However, the exergames have previously been found to elicit increased heart rates and moderate-intensity cardiovascular exercise.[2,8]

Statistical analyses

Descriptive statistics were calculated for all outcomes and demographic characteristics. To address our primary objective, one-way repeated measures analysis of variance (RM ANOVA) examined the effects of algorithm (OSFA, No-Balancing, GMFM Ability-Based) on the dependent variable, dyad spread. Bonferroni-adjusted pairwise comparisons were completed following significant overall effects. Nonparametric Friedman test examined the overall effect of algorithm on the perceived fun and fairness of the game. Following significant overall interaction, Wilcoxon signed-rank tests with Bonferroni corrections for multiple comparisons were used to evaluate differences between algorithms.

Results

Demographic information

Eight youth (two females; $\overline{X}$. age = 10.2 ± 2.2 years) participated in the study, all with bilateral spastic diplegic CP. Participants had GMFM-66 scores ranging from 25.2% to 87.4% (66.4% ± 17.8%). Seven participants were at Manual Abilities Classification System level I, and one at level II. Participants were evenly distributed between GMFCS levels II and III. Twenty-eight dyads raced and 22 had complete races for all 3 algorithms. Participants played the exergames for a total of 182 ± 20 minutes over the six intervention sessions. During the 30 ± 3 minutes/day of using the exergame, participants' heart rates were elevated, averaging 120 ± 8 beats per minute.

Calibration

After the first four calibration sessions, the threshold cadence for each participant was determined as per the least squares linear regression between their individual GMFM-66 score and average cadence during 30 seconds of intense racing (Fig. 1). Average cadence while racing was positively correlated to GMFM-66 score ($R^2 = 0.710$, $R^2_{adj} = 0.662$, $P = 0.004$).

Primary outcome

There was complete race data for all three algorithm conditions in 22/28 dyads. The RM ANOVA investigating dyad spread between algorithms was significant overall ($F_{2,42} = 40.85$, $P < 0.001$, $\eta_p = 0.66$, Fig. 2). Dyad spread was significantly lower when using GMFM Ability-Based balancing (4.6 ± 4.2) compared with No-Balancing (11.9 ± 6.8) ($P < 0.001$). When using the ideal balancing condition, OSFA, dyad spread was (1.6 ± 0.9), significantly lower than both GMFM Ability-Based ($P = 0.006$) and No-Balancing ($P < 0.001$).

Secondary outcomes

Participants agreed with the statement ''was that game fair?'' reflected by a median score of 4/5 for each algorithm.

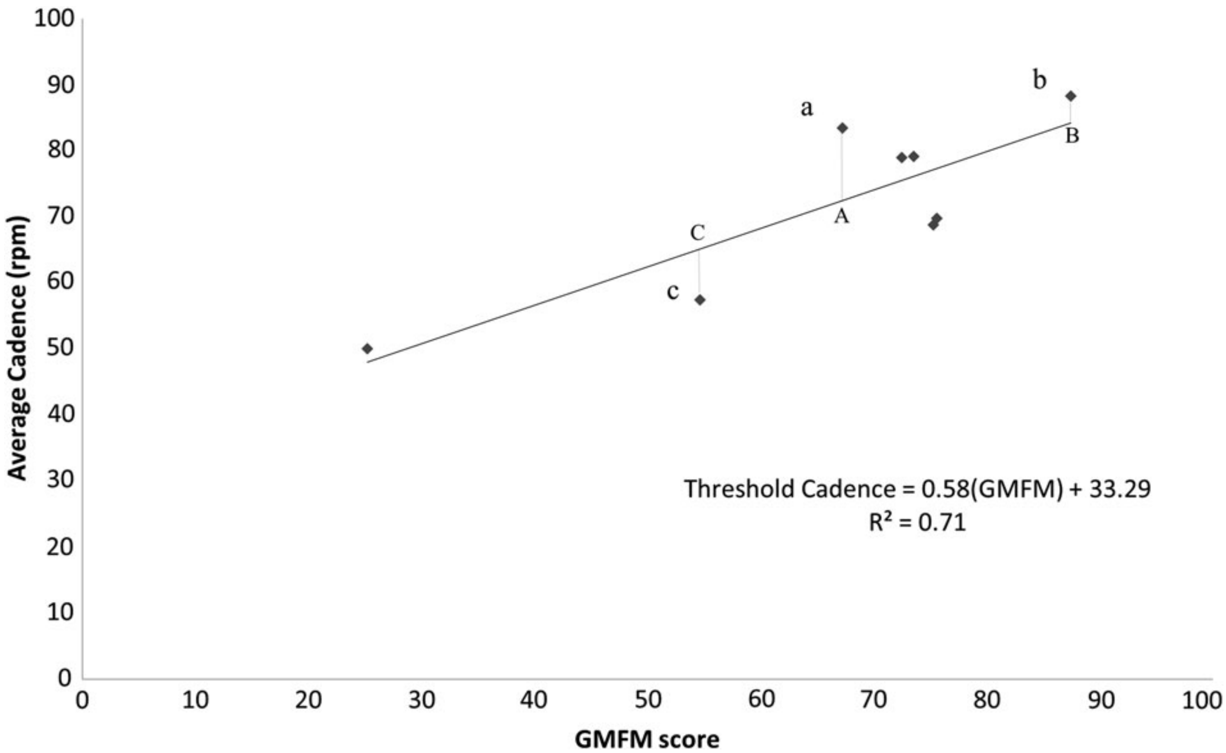

FIG. 1. Least squares linear regression between GMFM score and average cadence during 30 seconds of intense racing. Regression equation used to set threshold cadence for use in GMFM Ability-Based algorithm. Example of participants average recorded cadence (a–c) given with respect to their corresponding Threshold Cadence (A–C). GMFM, gross motor function measure.

No significant differences were found in the perceived fairness depending on the algorithm used (χ^2 [2] = 0.764, $P = 0.683$, Fig. 3). Participants also agreed with the statement ''was that game fun?'' with a median score of 4/5 for both No-Balancing and OSFA algorithms, and 3.5/5 for the GMFM Ability-Based balancing algorithm. The algorithm used affected the perceived fun experienced by participants (χ^2 [2] = 6.303, $P = 0.043$). However, *Post hoc* Wilcoxon signed-rank tests, with a Bonferroni corrected significance of $P < 0.017$, showed no differences between individual algorithms (Fig. 4).

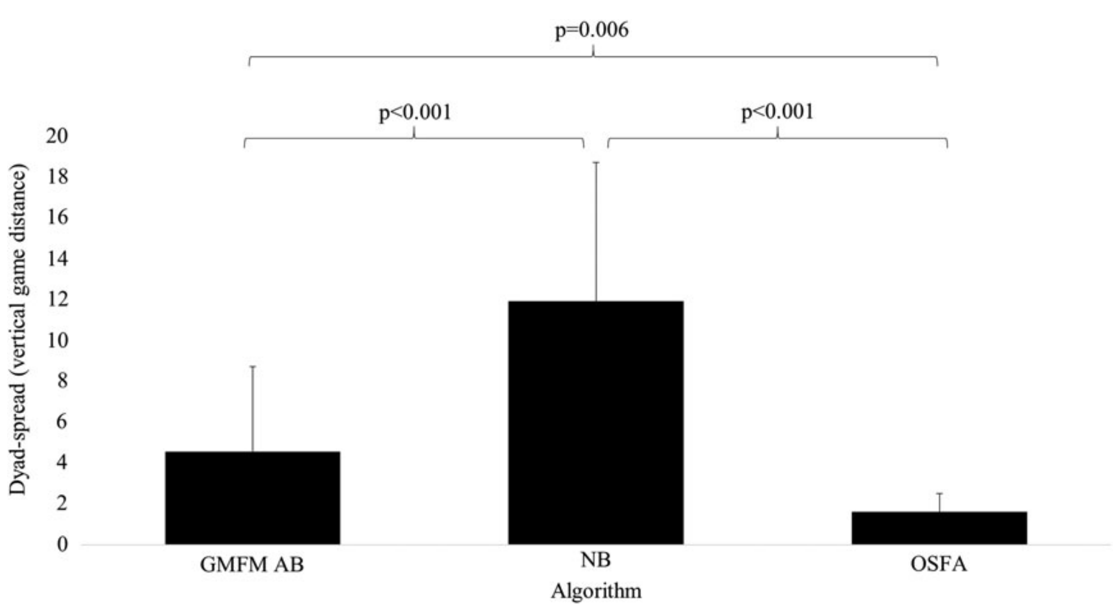

FIG. 2. Dyad Spread by algorithm indicating the smallest spread observed with OSFA, followed by GMFM Ability-Based and then NB. Overall repeated measures analyses of variance significant ($F_{2,42} = 40.85$, $P < 0.001$). OSFA, one-speed-for-all.

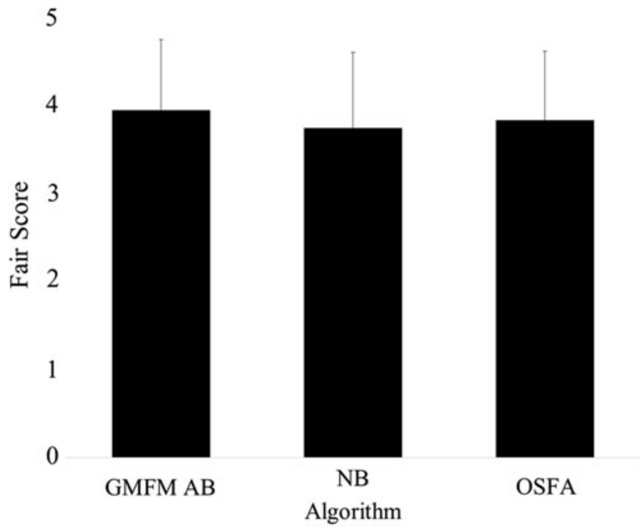

FIG. 3. Mean response to five-point Likert scale question ''was that game fair?'' taken after each algorithm. Overall significance (χ^2 [2] = 0.764, $P = 0.683$).

Discussion

In this prospective repeated measures intervention study, the suitability of the GMFM as a tool to facilitate opportunities for success in multiplayer exergames was evaluated. Youth with CP at GMFCS level II and III with GMFM-66 scores from 25.2% to 87.4% played a cycling-based multiplayer exercise videogame using a novel GMFM Ability-Based balancing algorithm. With the developed algorithm, the player spread decreased by 61% (from 11.9 to 4.6 game distance units) compared with the No-Balancing algorithm, thereby enhancing the opportunity for game success. As expected, the OSFA algorithm had the lowest player spread (1.6 game distance units), showing that improvements with the GMFM Ability-Based balancing algorithm are still possible. Lastly, all the balancing algorithms were rated as fun and fair.

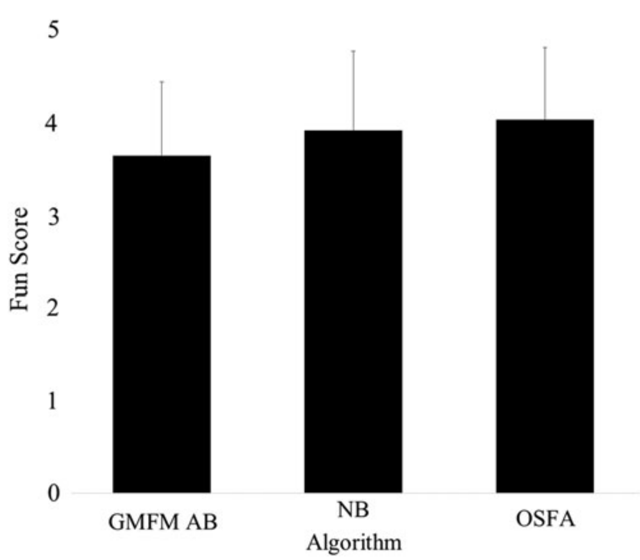

FIG. 4. Mean response to five-point Likert scale question ''was that game fun?'' taken after each algorithm. Overall significance (χ^2 [2] = 6.303, $P = 0.043$), with no *post hoc* significance with Bonferroni correction of $P < 0.017$.

Balancing algorithms are used to enhance interaction and competition by minimizing dyad spread (average distance between players). Providing players with opportunities for competition is a critical component to a motivational game framework.[13] Both the GMFM Ability-Based and OSFA algorithms lowered dyad spread. In the OSFA algorithm, average dyad spread was 1.6 game distance units, even though the algorithm sets the same speed for all players. A dyad spread of 1.6 game distance units could represent a baseline variability present in any race. This could be caused by participants choosing to stop pedaling momentarily midway through or at the end of the race. Dyad spread was three game distance units greater when using the GMFM Ability-Based algorithm (4.6) compared with the OSFA algorithm (1.6). Three game distance units equates to approximately one avatar length in the game. At one avatar length, players are well positioned to interact and compete (e.g., shoot and hit the opponent).

As hypothesized, dyad spread (average distance between players) was significantly lower with the GMFM Ability-Based algorithm, and lower still using the OSFA algorithm. This observation may lead to the conclusion that the OSFA algorithm should be implemented. However, there is no explicit motivation to pedal quickly when using the OSFA algorithm. This lack of motivation raises the concern that if participants play for longer periods of time or play from home, then they may only pedal enough to move their avatar, thereby decreasing the physical activity offered through the game. In the laboratory, participants appeared to pedal vigorously regardless of algorithm choice, likely due to the short duration, enhanced motivation of the group environment, and the standard encouragement administered by research staff. Future study is necessary to evaluate the effect of algorithms on player motivation and physical activity over extended time and in a home environment.

Using the GMFM-66 scores to adjust avatar speed leverages the concept of adaptive difficulty. Adaptive difficulty, where game environments are specific to each player,[14] has been implemented to change gameplay based on a variety of factors from player performance[15] to perceived anxiety.[16] Adaptive gaming has been an enjoyable and motivating tool in therapeutic exergames for individuals with CP,[17] stroke,[18] and Parkinson's disease.[19] To our knowledge, this is the first instance of applying adaptive difficulty based on gross motor function for multiplayer exergames in youth with CP. The results from the current study support the use of adaptive gaming to allow youth CP to engage in challenging and rewarding physical activity.

The GMFM score explained 66% of the variance in pedaling speed across youth with different physical abilities, during an intense 30-second bout of cycling. Confirming the strong relationship between GMFM score and pedaling cadence is encouraging, as it is commonly assessed in individuals with CP. However, cycling ability is also determined by perceived exertion, aerobic fitness, motivation, and body size among others.[20,21] These factors are also important when individuals with varying gross motor abilities play together. As the exergame becomes used by individuals with greater differences in ability (e.g., between GMFCS levels I and III), it will be important to ensure that GMFM scores partnered with average cadence continues to provide an appropriate correlation to cycling ability, and to adjust the relationship or incorporate new variables as needed.

Participants rated the exergames highly across all balancing algorithms in both fun and fairness. While the questionnaire was short and not from a standardized scale, our prior work using standardized scales has shown that the exergames are fun and fair.[2,8] Since the exergames have the potential to be used in the home, it is important to ensure they remain enjoyable to promote nonstructured physical activity. Biddiss et al. highlight the role of nonstructured opportunities for physical activity and its effect on weight management and fitness.[22] Provided the exergames remain enjoyable in a home-based environment, it would provide an outlet for physical activity without some of the conventional barriers to participation such as transportation and seasonal limitations.[23]

While minimizing distance between players facilitates competition, there are other important factors to consider for equal opportunities for game success, enjoyment, and physical activity. An individual's fine motor control (particularly to use a hand-held controller), visual-spatial coordination, and general skill or comfort with videogames warrant consideration when designing games that improve access to participation in physical activity. These factors affect how individuals use a controller to orient and guide themselves through the game world. Our research team is currently investigating ways to improve play across individuals not only with disparate gross motor but also fine motor abilities.

This study demonstrates that the GMFM-66 is a viable tool to use in adaptive gaming to allow youth with CP at different levels of physical ability to play cycling-based exergames together. With the GMFM Ability-Based balancing algorithm, player spread was reduced significantly, which can allow players to stay near one another. The potential next steps developing and refining the GMFM Ability-Based algorithm includes: testing the impact of algorithm in a home-based environment, testing the GMFM Ability-Based algorithm across individuals with wider gross motor abilities, and testing in different game types (i.e., collaborative games). To ensure that exergames remain a motivational and an enjoyable option for physical activity, future work is also aimed at incorporating other factors into balancing for people with different abilities. These factors include: fine motor control, visual-spatial coordination, and gaming experience. By improving opportunities for successful game interactions, the GMFM Ability-Based balancing algorithm should help youth with CP participate in physical activity through exergaming.

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Declaration of Interest Statement

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Author Disclosure Statement

D.L.F., T.C.N.G., L.S., D.C., S.H., A.S., and A.M. have intellectual property interest surrounding the Liberi Exergame.

References

1. Maher CA, Williams MT, Olds T, Lane AE. Physical and sedentary activity in adolescents with cerebral palsy. Dev Med Child Neurol 2007; 49:450–457.
2. Knights S, et al. An innovative cycling exergame to promote cardiovascular fitness in youth with cerebral palsy: A brief report. Dev Neurorehabil 2014; 19:135–140.
3. Warburton DER, et al. The health benefits of interactive video game exercise. Appl Physiol Nutr Metab 2007; 32: 655–663.
4. Maloney AE, et al. A pilot of a video game (DDR) to promote physical activity and decrease sedentary screen time. Obesity 2008; 16, 2074–2080.
5. Hernandez HA, Ye Z, Graham TC, et al. Designing action-based exergames for children with cerebral palsy. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* Paris: ACM; 2013, pp. 1261–1270.
6. Hernandez HA, et al. Design and evaluation of a networked game to supportsocial connection of youth with cerebral palsy. In *Proceedings of the 16th International ACM SIGACCESS Conference on Computers & Accessibility—ASSETS'14*. Rochester, NY: ACM Press; 2014.
7. Rosenbaum PL, Palisano RJ, Bartlett DJ, et al. Development of the gross motor function classification system for cerebral palsy. Dev Med Child Neurol 2008; 50: 249–253.
8. MacIntosh A, et al. Balancing for gross motor ability in exergaming between youth with cerebral palsy at gross motor function classification system levels II and III. Games Health J 2017; 6:104–110.
9. Stach T, Graham TC, Yim J, Rhodes RE. Heart rate control of exercise video games. In *Proceedings of Graphics interface 2009.* Kelowna, BC: Canadian Information Processing Society; 2009, pp. 125–132.
10. Russell D, Rosenbaum P, Avery L, Lane M. *Gross Motor Function Measure (GMFM-66 and GMFM-88) User's Manual*. Cambridge University Press; 2002.
11. Beckung E, Carlsson G, Carlsdotter S, Uvebrant P. The natural history of gross motor development in children with cerebral palsy aged 1 to 15 years. Dev Med Child Neurol 2007; 49:751–756.
12. Hernandez HA, et al. Design of an exergaming station for children with cerebral palsy. In *Proceedings of the 2012 ACM Annual Conference on Human Factors in Computing Systems—CHI'12.* Austin, TX: ACM Press; 2012, p. 2619.
13. Yee N. Motivations for play in online games. Cyberpsychol Behav 2006; 9:772–775.
14. Denisova A, Cairns P. Adaptation in digital games. In *Proceedings of the 2015 Annual Symposium on Computer-Human*

Interaction in Play—CHI PLAY'15. London: ACM Press; 2015, pp. 97–101.

15. Yun C, Trevino P, Holtkamp W, Deng Z. PADS. In *Proceedings of the 5th ACM SIGGRAPH Symposium on Video Games—Sandbox'10*. Los Angeles, CA: ACM Press; 2010, pp. 31–36.
16. Liu C, Agrawal P, Sarkar N, Chen S. Dynamic difficulty adjustment in computer games through real-time anxiety-based affective feedback. Int J Hum Comput Interact 2009; 25, 506–529.
17. Bryanton C, et al. Feasibility, motivation, and selective motor control: Virtual reality compared to conventional home exercise in children with cerebral palsy. Cyberpsychol Behav 2006; 9:123–128.
18. Ma M, et al. Adaptive virtual reality games for rehabilitation of motor disorders. Lect Notes Comput Sci 2007; 4555:681–690.
19. Smeddinck J, Siegel S, Herrlich M. Adaptive difficulty in exergames for Parkinson's disease patients. Graph Interface Conf 2013 2013; 141–148.
20. Adamo KB, Rutherford JA, Goldfield GS. Effects of interactive video game cycling on overweight and obese adolescent health. Appl Physiol Nutr Metab 2010; 35: 805–815.
21. Marsh A, Martin P. Perceived exertion and the preferred cycling cadence. Med Sci Sports Exerc 1998; 30:942–948.
22. Biddiss E, Irwin J. Active video games to promote physical activity in children and youth: A systematic review. Arch Pediatr Adolesc Med 2010; 164:664–672.
23. Zabinski MF, Saelens BE, Stein RI, et al. Overweight children's barriers to and support for physical activity. Obes Res 2003; 11:238–246.

Address correspondence to:
Darcy L. Fehlings, MD
Holland Bloorview Kids Rehabilitation Hospital
150 Kilgour Road
Toronto M4G 1R8
Ontario
Canada

E-mail: dfehlings@hollandbloorview.ca