How Game Balancing Affects Play: Player Adaptation in an Exergame for Children with Cerebral Palsy

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ABSTRACT
Player balancing helps people with different levels of physical ability and experience play together by providing customized assistance. Player balancing is particularly important in exergames, where differences in physical ability can have a large impact on game outcomes, and in making games accessible to people with motor disabilities. To date, there has been little research into how balancing affects people's gameplay behaviour over time. This paper reports on a six-day study with eight youths with cerebral palsy. Two games incorporated algorithms to balance differences in pedaling ability and aiming ability. Balancing positively impacted motivation versus non-balanced conditions. Even in "blowout" games where one player won by a large margin, perceived fun and fairness were higher for both players when a player balancing algorithm was present. These results held up over six days, demonstrating that the results of balancing continued even after players had the opportunity to understand and adapt to the balancing algorithms.

Author Keywords
Game balancing; exergame; active video game; player balancing; video game design.

ACM Classification Keywords
K.8.0. General: Games.

INTRODUCTION
Players of video games have different levels of ability, affecting how well they are able to play. Game-playing ability is multi-factorial: in addition to personal experience, players' performance in a given game might be affected by physical abilities like manual ability and reaction time, or abilities in cognitive tasks such as spatial reasoning, forming tactics, strategy, and pattern matching [12].

When players need to perform vigorous physical activities, such as when playing exergames, physical fitness [21] influences game-playing success. Physical abilities are particularly important for children with motor disabilities, who may be less adept than typically-developing children in activities such as running, jumping, or pedaling a bicycle.

Player balancing alters game mechanics to assist players with weaker abilities [4,8]. In the general population, balancing algorithms are helpful; among people with physical disabilities, they are critical. Previous research has investigated techniques for player balancing. However, little is known about how players' behaviour in games changes over time in response to balancing algorithms. For example, do players change how they play after they have had time to understand the effects of balancing algorithms? How does the presence or absence of player balancing in games affect players' motivation, effort, and other gameplay behaviours? Do the effects of balancing on player behaviour persist or change over time?

We are interested in whether the effect of balancing algorithms for people with disabilities is transient, or whether balancing can work over the longer term to make exergames more accessible to groups with differences in physical ability.

To address these questions, we ran a study of eight youths with cerebral palsy (CP) playing two test exergames over six days. These exergames were designed to test two core areas of difference between children with CP: gross motor function, and fine motor function. Gross motor function was tested in a cycling-based racing game, while fine motor function was tested in a shooting game. Participants played each game in pairs, giving a total of 28 distinct pairings of the eight participants.

The key results of this study are:

- Balancing for physical ability both increased player motivation and reduced the number of "blowout" races where one player performed vastly better than the other.

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- Perception of fun and fairness was unaffected overall, but in races that were blowouts, both winners and losers considered gameplay both more fun and more fair with balancing algorithms applied.
- Balancing increased players' accuracy in the shooting game, but their rate of fire was unchanged.
- These differences held up across the 6 days of the study.

We begin with an overview of game balancing techniques and research on player perceptions of balancing. We then provide the context of the research, design of the study, and overviews of the two games used for testing. Finally, we present the results of the study, discussion and analysis of results, and implications for design.

RELATED WORK

A body of research has developed over recent years in algorithms for balancing games, and in understanding how players react in the presence of such algorithms.

Game Balancing

Balancing in multi-player games can be difficult because skill is multi-factorial, including but not limited to prior experience, reaction time, and fine motor control [3,23]. Skill imbalance arises when the skill level between players varies, which can result in weaker players becoming frustrated at the game and stronger players becoming bored at the lack of challenge [8]. Skill imbalance is particularly pronounced when some players have motor disabilities [11,24].

Player Balancing Mechanisms

Prior research into player balancing mechanisms has identified four distinct approaches: difficulty adjustment, matchmaking, asymmetric roles, and skill assistance.

Difficulty adjustment

Difficulty adjustment matches the level of challenge in the game to the player's ability [4,6,16,22,23], and can be static or dynamic in nature. Static difficulty adjustment is typically based on predetermined difficulty levels or handicaps applied to the stronger player, while dynamic algorithms involve performance-based difficulty adjustments. In multi-player games, difficulty adjustment algorithms balance the level of challenge presented to the player by adjusting mechanics affecting the performance of the players [1]. For example, the lightning bolt item in *Mario Kart Wii* has a longer effect on racers closer to first place [25].

Matchmaking

Matchmaking systems balance by ranking player skill using a rating system, and then grouping players of similar rank together [4,6,22,23]. Matchmaking systems are core to the gameplay of competitive multi-player games like *League of Legends* [26]. However, these systems require a large pool of players with different skill levels in order to accurately place players [4]. Temporary fluctuations in performance (e.g., an unlucky series of losses) can have a severe impact on a player's rank [6,22], and it is not always possible to find an exact match to a team or personal rank.

Asymmetric roles

In games with asymmetric roles, player balancing occurs naturally when players select roles that suit their level of expertise [4,6,22,23]. In Blizzard's *Overwatch*, heroes are grouped into four roles [27], with each hero having different responsibilities and play styles. Even if players lack the skill to perform certain tasks, they can still contribute to their team's success by choosing roles that play into their strengths. However, players may be forced into playing specific roles [6], leaving them unable to practice the skills they need to branch out into different roles.

Skill Assistance

Skill assistance compensates for lower ability by making it easier to correctly perform in-game actions [4,6,23]. These skills vary depending on the game. For example, in the racing game *Forza Motorsport 4*, players can turn on steering, braking, and stability assists to improve their performance. Most research in skill assistance has been in aim assistance, which reduces the accuracy required to acquire a target [6,23], making it easier for the player to score hits [22]. Two aim assistance strategies that have been shown to be effective in stylized [3] and realistic [23] shooting games are bullet magnetism [8,23] and area cursors [22,23]. Prior studies found that aim assistance provided a more enjoyable experience for all players [3,22]. Experiments have suggested that balancing does not limit the rate at which players develop gaming skills [9].

Balancing Exergames

When balancing exergames (games that incorporate physical exercise) [12,15], designers need to account for differences in physical ability [7,16]. The balancing problem requires designers to account for differences both in player skill levels and physical ability [20].

Balancing between disparate fitness levels

Prior research has shown that multi-player exergames can be balanced by basing in-game performance on the player's physical effort [13,16,21]. Heart rate has been used as a measure of effort in jogging-based exertion games [16] and pedaling-based exergames [21], allowing people with different fitness levels to compete and play together.

Accessibility and Video Games

While game balancing attempts to address skill imbalance, game accessibility attempts to open games to a broader audience [28]. Players with disabilities may have deficits in how they perceive stimuli, determine responses, or provide input in video games [24]. This can exclude players with disabilities from many of the games they would like to play. Motor disabilities are the farthest-reaching category of impairment, affecting a significant percentage of persons with disabilities [28]. They may find conventional game controllers difficult to use due to impaired fine motor control [10–12]. Inputting time-sensitive commands, or having to input multiple commands at once may be too difficult.

Exergames present particular challenges to accessibility, as some players may be unable to perform the physical actions

– such as pedaling, jumping or running – required by the exergame [10]. In exergames, player balancing becomes especially important because differences in physical ability affect game outcomes.

Accessibility strategies (e.g., simplifying input by using contextual actions [12]) can inform player balancing, and allow games to be played by gamers with and without disabilities [24,28]. Gerling *et al*. have shown that players without disabilities and players using wheelchairs could compete in a dance exergame [7]. But to date, there has been little work in player balancing for persons with disabilities, particularly on balancing for disparate levels of physical ability in multi-player games. Many commercial games provide design features such as remappable keys to accommodate disabilities, but few provide balancing specifically for players with disabilities.

Effects of Balancing on Players

In determining what strategies to use for balancing, it is important to understand how players perceive and change their behaviour in response to balancing approaches.

Perceived competence and self-esteem

Prior research indicates that players' perception of balancing largely depends on their awareness of in-game assistance [1,6,7]. Short-term studies have shown that balancing usually increases perceived competence in weaker players without negatively impacting stronger players [20,22].

Player experience and perception of games with balancing

How players respond to balancing depends on the visibility of the assistance [6] and play setting. In social play, players are more accepting of assistance because it promotes playing together with friends who may have disparate skill levels [6]. In social play, the use of skill assistance can lead to increased engagement [6] and can enable players with extreme ability differences to compete without reducing the fun of stronger players [7,3]. Research also suggests that weaker players tend to want their receipt of assistance to be concealed from others while stronger players prefer full disclosure [1]. In addition, stronger players are more accepting of assistance in a social multi-player setting [6].

Balancing algorithms have been shown to improve play experience and perception of fairness in single-session studies [3]. Little is known about player reaction to balancing algorithms over a longer timeframe. Gutwin *et al.* have shown that skill assistance does not hinder the development of skills over time [8], which may be promising to designers who fear players becoming overly reliant on assistance.

CONTEXT

This research was performed in the context of the two-week SportFit summer camp for children with cerebral palsy (CP), held at a children's rehabilitation hospital. CP is a neurological disorder causing a broad range of motor disabilities [9–12]. Children with CP often experience decline in gross motor function as they transition to adulthood [9,10,12]. This decline is multifactorial, but significant contributors are poor physical fitness, muscle weakness due to disuse, changes in body composition, limitations in range of motion, and pain [10,12].

The camp aimed to improve the cardiovascular fitness of the participating children, and promote gross motor recreational activity participation. Prior research [9,10] suggests that moderately to vigorous physical exercise, such as that encouraged through exergaming, promotes an improvement in cardiovascular fitness.

As one of the camp's activities, children played one hour per day of the cycling-based Liberi exergame [11]. This allowed us to observe participants' impressions of and behaviour toward balancing algorithms over a two-week period, addressing the question of whether behaviour changes as players become aware of the algorithms' properties. To isolate balancing from other factors, we included daily play of two custom-designed games focusing on balancing of gross motor function (Gekku Pedal) and aiming skills (Gekku Aim). Our study was run under the aegis of the hospital's research ethics board.

Impact of Cerebral Palsy on Balancing

The motor disabilities present in CP impact performance in exergames such as Liberi. Deficits in gross motor function impact pedaling ability; deficits in visual-motor integration and processing and fine motor control impact the aiming tasks used, for example, for shooting and navigating in games. Gross motor function in people with CP is categorized by the Gross Motor Function Classification System (GMFCS) [17–19], ranging from limited impairment at level I to severe impairment at level V. SportFit attendees were all at GMFCS level II or III. But even within these levels, there is a wide range of function. People at GMFCS level III use mobility devices, which may range from hand-held walkers to motorized wheelchairs. At level II, people are able to climb stairs holding a railing, but may or may not use mobility devices.

In multiplayer games, people with CP have a particular need of algorithms that compensate for differences in motor ability because there is significant variation in individual fine and gross motor ability [17–19], which presents a challenge to children playing together with their peers [11,14]. This balancing challenge is compounded by the lack of availability of accessible action-based exergames. Therefore, we designed our own test games to compare the impacts of players' fine and gross motor ability.

TEST GAMES

To test balancing for gross motor function (GMF) and for fine motor function, we needed to be able to separate their effects on game outcomes. We did this by creating two separate test games.

Gekku Pedal is a racing game whose outcome is decided by gross motor function and player effort. Gekku Aim is shooting game, based on aiming skills and fine motor function. These games were created using assets from the Liberi game Gekku Race, featuring cartoon lizards called “gekkus”. Intentionally, little gameplay skill is required by these two games, which allows us to observe imbalance that arises from different levels of gross and find motor function. Because the difference in physical abilities is great among people with CP, imbalance between players in this population is visible, allowing clear perception of how well a balancing algorithm is functioning.

For these trials, we were interested in players’ perceptions of and adaptations to the balancing algorithms. We therefore made the effects of the algorithms obvious, to increase the likelihood of players understanding over time that balancing was being used, and subsequently adapting their behaviour to the algorithm. In terms of Mueller *et al.*'s framework for creating balanced exertion experiences [15], this can be expressed as strongly *explicit* rather than *hidden* presentation. The algorithms we used are also controlled by the *designer* rather than the *user*, and use *static* rather than *dynamic* adjustment, to simplify the algorithms and enable us to focus on player's reactions to the balancing.

We adopted the conventions of the Liberi exergame being used in the study. Players are seated at a custom-designed bicycle [10], and pedal to move their avatar (see Figure 1 for the exergame hardware setup). The game world is shown on a screen mounted in front of the player’s bicycle. Players use a handheld video game controller to steer their avatar through the world, and to activate in-game actions.

Gekku Pedal

To test gross motor balancing, we created Gekku Pedal (see Figure 2 left). In Gekku Pedal, two players race their “gekku” lizards up a wall. The first to reach the top is the winner. Gekkus run straight up, so the winner is determined by pedaling speed.

In the non-balanced version of Gekku Pedal, players’ pedaling cadence is linearly mapped to the gekkus’ forward speed. The faster the player pedals, the faster the gekku runs toward the finish line. In the balanced version, gekkus move at only one speed. If the player is pedaling at all, then the gekku runs forward at this constant speed. Since any pedaling cadence results in the same speed, differences in gross motor function have no effect, as long as players are able to pedal.

Figure 1: Youth with CP seated on custom-built recumbent bicycle with pedaling attachments and lateral supports.

We adopted this extreme balancing approach to increase the visibility of the algorithm to the players. We expected that players would realize that they could pedal less vigorously, since increased effort did not influence the chance of winning. We also expected that some players might find the algorithm to be unfair, as increased effort is not rewarded.

Gekku Aim

Players’ reaction to the presence of balancing for aiming ability was tested using the Gekku Aim game (see Figure 2 right). Gekku Aim is a two-player game, where players attempt to hit their opponent by spitting cashews. The winner is the player who has the highest number of hits within the one-minute duration of the game. When the game starts, gekkus automatically move up the track at a set speed. Players shoot cashews by aiming with the joystick and pressing any of the buttons on the controller to fire. When a gekku lizard is hit, it becomes invisible and teleports to a random nearby location before becoming visible again, requiring both players to re-acquire their target.

Figure 2: In Gekku Pedal (left), players pedal a bike to move their avatar up the track; the first to the top of the track wins the race. In Gekku Aim (right), players shoot other players by aiming at them and pressing a button to fire a cashew.

Balancing in Gekku Aim is aided by a bullet magnetism aim assistance algorithm [22,23]. When aim assistance is not active, the cashews travel in precisely the direction the shooting player is aiming, whether or not that shot will result in a hit. With aim assist on, the game checks in an area around where the shooter is aiming. If an opponent is within that area, the cashew shoots in the direction of that opponent.

This algorithm is static rather than dynamic, in that it provides all players with the same assistance. We nevertheless expected the algorithm to favour players with weaker aiming skills, as they are more likely to be pointing in the wrong direction. We also intended that players would understand the effect of the algorithm over time, realizing that at times the cashew moved directly toward the opposing gekku despite their aiming in the wrong direction.

STUDY DESIGN

During the two-week SportFit camp, one hour a day was set aside for participants to exercise by playing exergames. During this time, participants played the balanced and non-balanced versions of Gekku Pedal and Gekku Aim in pairs. When not engaged in the study games, participants played Liberi for fun. Participants were allowed to stop at any time. The first four days of the SportFit camp were devoted to calibration of the games and familiarization of the participants with the equipment. Study data was collected on the remaining six days of the camp.

Research Questions

The study addressed three primary research questions:

RQ1: *Do the balancing algorithms reduce differences in players' performance?* We hypothesized that the presence of balancing algorithms would reduce differences between players in game outcomes.

RQ2: *How does the presence or absence of a balancing algorithm affect player behaviour and player perception?* We hypothesized that players might pedal more slowly or shoot less, because they feel their efforts have less effect. Also, players might feel that balancing makes the game more fun to play, or that more balanced games are more fair.

RQ3: *How do these effects persist or change over time?* We were interested in understanding how players perceived balancing over time, and how their behaviour would adapt once they had recognized and understand the properties of the in-game balancing algorithms over two weeks of play.

Participants

Study participants were children with CP who were clients of Holland Bloorview Kids Rehabilitation Hospital, where the study took place. Participants were invited, with their parents'/guardians' permission, to participate in our study. Recruitment parameters were: 8-14 years old, GMFCS level II or III, and able to operate a hand-held videogame controller. Exclusion criteria were orthopedic surgery within the last three months, or health conditions counter-indicating play of exergames.

A total of eight participants (2 female) were recruited for the study, with a mean age of 10.2 ± 2.2 years. The participants were evenly distributed between GMFCS levels II and III. Three participants had played Liberi previously. All youth were able to actively participate in the games and the intensive therapy protocols, and were able to engage well with their peers and other SportFit camp participants.

Equipment

Participants played the games using a Logitech F710 wireless gamepad, and a custom-designed stationary recumbent exercise bicycle (see Figure 1 for hardware setup). The game client itself ran on a 23” screen all-in-one computer. Participants wore Polar chest-strap heart rate monitors. For reasons of data security, the games were hosted on a closed LAN. Each client machine was connected through an Ethernet router to a server computer, operated by a researcher overseeing play.

Measures

In this section, we describe the measures used to capture effectiveness of the balancing algorithms, player behaviour, and player perception.

Effectiveness Measures

Spread is the difference between the two players' performances in a game. We consider low spread to be an indication that the game was balanced.

- In Gekku Pedal, spread is the average vertical distance between players across the first 19 seconds of the race (the duration of the shortest recorded race).
- In Gekku Aim, spread is the difference in final score, measured as the higher score minus the lower score.

Blowouts are games in which one player was very far ahead of the other. The losing player has fallen so far behind that they had no hope of catching up. The *blowout rate* is then the number of blowouts divided by the total number of games played. A good balancing algorithm reduces blowout rates.

- In Gekku Pedal, we consider a race to be a blowout if one player is so far ahead that the trailing player cannot see the other's gekku (see Figure 3) for at least three consecutive seconds.

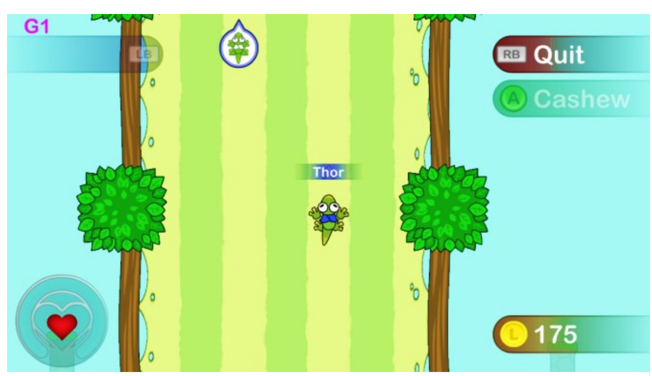

Figure 3: A blowout race in Gekku Pedal. The leading player is so far ahead as to no longer be visible on screen.

- In Gekku Aim, we consider a game to be a blowout if the winning player's score is more than 50% higher than the losing player's score.

Hit rate in Gekku Aim is the number of times the player hit their opponent during the race, divided by their total number of shots. This is a primary measure of players' success in the balanced/non-balanced conditions.

Behaviour Measures

Player behaviour was monitored by the researchers overseeing play. We also included two quantitative measures, one for each game:

- *Average cadence* in Gekku Pedal is a player's mean cadence, used as a measure of player effort.
- *Fire rate* in Gekku Aim is a player's average number of cashews shot per second, calculated as number of cashews shot divided by total number of seconds. This is used as a measure of how much a player is trying to win (inverse measure of player conservatism).

Player Perception Measures

Players' perceptions were gathered through two questions rated on five-point Likert scales:

- *Fun* is participants' answers to the question "was that game fun?"
- *Fairness* is participants' answers to the question "was that game fair?"

In previous studies, we have found that asking too many or overly detailed questions often led to young players losing focus and answering haphazardly. These questions are intentionally simple to avoid this problem.

Method

Due to a limited number of cycling stations, the eight participants were divided into two groups of four. To ensure that every participant played the test games with each other participant, a player from each group was switched with one from the other each day, for a total of 28 distinct player pairs for each game. Participants played for a total of one hour per day. When not engaged in playing Gekku Aim or Gekku Pedal, players had free-play time where they could choose which Liberi games to play.

Each pair of participants played all four test conditions – both test games, both with and without balancing – back-to-back. Test games were run starting with Gekku Pedal and alternating with Gekku Aim, to allow players to rest in between rounds of Gekku Pedal. The order in which the test conditions were run was otherwise order-balanced to include all possible sequences.

The SportFit camp ran for 10 days over two weeks. We began our study on day five of the camp, resulting in six days of data. For examination of whether results varied over time, we considered separately the first two days, capturing initial impressions. From the final four days, we captured longer-term impressions. Testing prior to the study determined the appropriate mapping of cadence to in-game speed for the non-balanced condition of Gekku Pedal, based on all participants' average cadence across the calibration period.

Data Collection

Data for measuring spread, blowouts, hit rate and fire rate, and average cadence were captured quantitatively within the games and written to log files. These log files were transferred to a secure offline database. The measures were then computed by an analysis program polling the database and generating tables containing the desired measures. The tables were imported into IBM SPSS v24 for analysis.

Players' perceptions of whether games were fun and fair were obtained with a Likert scale questionnaire by the three observers supervising the participants. The questionnaire was applied following each round of the game.

The observers also collected data on participant behaviour by recording instances of players noticing the difference between the balanced and non-balanced conditions. To distinguish between players' initial impressions and their longer-term impressions, we compared players' behaviour observed in the first two days of the study (early) to behaviour observed in days three to six (late).

RESULTS

We present our results around our research questions about game outcome, play behavior and player perception of balancing algorithms over time. Alpha for significance was set at .05. When applied, Bonferroni correction is reported as an adjustment to this alpha threshold rather than as adjustments to the p-values. To avoid assumptions around the shape of the data, all ANOVAs were conducted using Greenhouse-Geisser correction. To capture effect size, we report Cohen's d values; Cohen suggests that d=0.2 indicates a small effect; d=0.5 indicates a medium effect, and d=0.8 indicates a large effect [5].

RQ1: Effectiveness of Balancing

We first examined the degree to which the balancing algorithms employed in the Gekku Pedal and Gekku Aim games reduced differences in player performance.

Gekku Pedal: effectiveness of gross-motor balancing

To test how gross-motor balancing affected player performance, we analyzed spread (average difference in position) and blowout rate.

A paired-samples t-test showed that average spread between players was lower in the balanced condition (M=1.57, SD=0.894) than in the non-balanced condition (M=10.39, SD=6.25); $t(27)=7.46$, $p<.001$, d=1.98. In the non-balanced condition, the blowout rate was close to 90% (M=.886, SD=.318), compared to zero in the balanced condition (M=.000, SD=.000); $t(68.5)=-23.3$, $p<.001$.

Gekku Aim: effectiveness of fine-motor balancing

To see how the presence of aim assistance for balancing affected player performance, we considered hit rate, spread (average difference in score), and blowout rate.

A t-test showed that players had a higher hit rate in the aim assistance condition (M=.781, SD=.126), than in the no aim assistance condition (M=.629, SD=.214); t(7)=8.09, p<.001, *d*=1.26. Player hit rate without aim assistance was found through linear regression to be correlated with improvement in hit rate in the aim assistance condition (see Figure 4); R=.889, p=.003.

A t-test showed that players had higher scores in the presence of aim assistance (M=15.7, SD=3.39) than without aim assistance (M=12.2, SD=4.10); t(7)=9.57, p<.001. However, there was no significant difference in average score spread between the aim assistance (M=6.10) and no aim assistance (M=6.95) conditions; t(27)=1.03, p=.311. Without aim assistance, more than half of the games played were blowouts (M=.536, SD=.508). In the presence of aim assistance, the number of blowout games dropped by almost 50% (M= .286, SD=.460); t(27)=-3.00, p=.006.

RQ2: Effect on Player Behaviour and Player Perception

Having established that the balancing algorithms improved player performance, our next question asked whether the presence of balancing affected the way people play, or affected their perceptions of the game's fun and fairness.

Gekku Pedal: behavioural effect of gross-motor balancing

To evaluate how balancing affected the level of effort players put into pedaling, we compared players' average cycling cadence. A t-test showed that players pedaled harder in the presence of balancing (M=70.9 RPM, SD=21.6) than when no balancing algorithm was used (M=58.5 RPM, SD=22.9); t(7)=-4.02, p=.005, *d*=.556.

With cadence considered separately between non-balanced blowout races, non-balanced non-blowout races, and balanced condition races (all non-blowouts), an RM-ANOVA showed a significant within-subjects effect; F(1.28, 7.70)=8.46, p=.017. Post-hoc pairwise comparisons (see Figure 5) showed that cadence was lower in non-balanced blowouts (M=57.7, SD=25.3) than in balanced races (M=70.7, SD=23.3); p=.014, *d*=0.532.

Cadence was not significantly different between non-balanced non-blowouts (M=68.1, SD=26.1) and balanced races; p=.188. There was an apparent difference between blowouts and non-blowouts in the non-balanced condition, but the difference was not significant at the Bonferroni-corrected alpha=.05/3 level; p=.041. One of the participants only had blowout races in the non-balanced condition, and so was excluded from this analysis.

Gekku Aim: behavioural effect of fine-motor balancing

Our primary measure for whether player behaviour changed in the presence of balancing or over time is fire rate. Players might fire more quickly, allowing aim assistance to compensate for the resulting loss of accuracy. T-tests showed there was no difference in players' fire rates between games with aim assistance (M=.330) and games with no aim assistance (M=.325); t(7)=1.10, p=.306.

Gekku Pedal: perceptual effect of gross-motor balancing

Participants' five-point Likert scale responses to whether they found the games fun or fair were analyzed through 2x2 repeated measures ANOVAs, according to presence/absence of balancing and to whether the responding player had won or lost the race.

Ratings of fun were not significantly different between balanced (M=4.09) and non-balanced (M=3.96) conditions; F(1,21)=0.475, p=.498. There was also no significant difference in responses between the winners (M=4.23) and losers (M=3.82); F(1,21)=2.78, p=.110.

Responses for fairness were not significantly different between balanced (M=3.84) and non-balanced (M=3.75) conditions; F(1,21)=.164, p=.690. No significance was found between the winners (M=3.93) and losers (M=3.66); F(1,21)=1.08, p=.311.

Gekku Aim: perceptual effect of fine-motor balancing

Participants did not report a difference in fun between the aim assistance (M=3.78) and no aim assistance (M=3.80) conditions; F(1,22)=.004, p=.950. There was likewise no difference in fun between winners (M=3.72) and losers (M=3.87); F(1,22)=1.43, p=.245.

Perceived fairness was not different between aim assistance (M=3.67) and no aim assistance (M=3.63) conditions; F(1,22)=.015. Fairness was not different between winners (M=3.65) and losers (M=3.65); F(1,22)=.000, p=1.00.

To test what effect blowouts had on players' perceptions of the game, we repeated these tests using data from blowout games only (this could not be done for Gekku Pedal, as there were no blowouts in the balanced condition).

Participants rated blowouts as more fun with aim assistance (M=4.06) than in the no aim assistance condition (M=3.81); F(1,7)=7.00, p=.033. Blowouts were also considered more

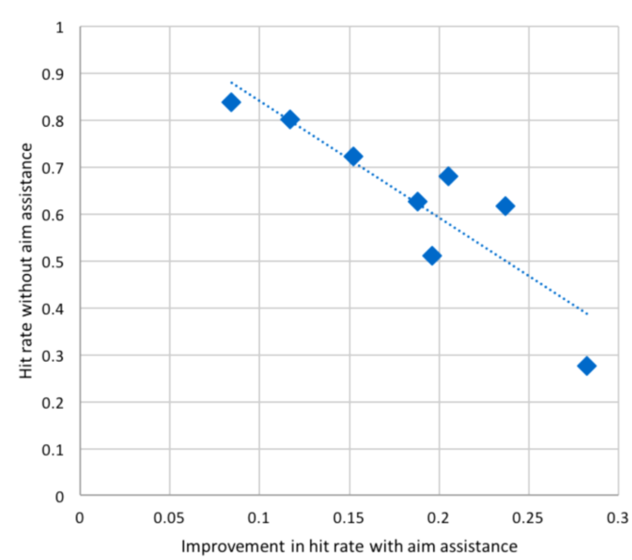

Figure 4: Linear regression of players' initial hit rates versus their aim-assisted hit rate.

fun by the winners (M=4.50) than the losers (M=3.38); F(1,7)=5.97, p=.045. No significant interaction was found between assistance condition and winner/loser; F(1,7)=1.40, p=.275. (See Figure 6 right).

Participants considered blowouts to also be more fair in the aim assistance condition (M=4.00) than in the no aim assistance condition (M=3.56); F(1,7)=8.80, p=.021. Blowouts were not considered significantly more fair by winners (M=4.25) than by losers (M=3.31); F(1,7)=2.63, p=.149. No interaction was observed between condition and winner/loser; F(1,7)=.127, p=.732. (See Figure 6 left).

RQ3: Persistence of Effects Over Time

Finally, we were interested in whether the identified behavioural changes persisted over time.

Gekku Pedal: persistence in gross-motor balancing behavior

Average pedaling cadence over the course of the study was examined through a 2x2 RM-ANOVA using time during study and balancing condition as within-subjects factors. No significance was found between early (M=64.5) and late (M=65.3) races; F(1,7)=0.0542, p=.823. No significant interaction was found between time during study and balancing condition; F(1,7)=1.36, p=.281.

Gekku Aim: persistence in fine-motor balancing behavior

A 2x2 RM-ANOVA examining fire rate was conducted, with time during study and balancing condition as factors. No significance was found between early (M=.325) and late (M=.333) games; F(1,7)=.561, p=.476. No significant interaction was found between time during study and balancing condition; F(1,7)=1.20, p=.309.

A second 2x2 test was run for hit rate, again with time during study and balancing condition as within-subjects factors. No significant difference was found between early (M=.722) and late (M=.727) games; F(1,7)=.027, p=.874. No interaction was found between time and condition; F(1,7)=.296, p=.603.

DISCUSSION

This study was designed to test the effects of employing balancing in exergames for both gross motor function and fine motor function, in a population (people with CP) with wide variability in both. Our primary areas of inquiry were to confirm that the balancing algorithms functioned, to examine how presence or absence of balancing affected players' behaviour and perceptions, and to investigate whether these effects varied over several days of play.

RQ1: Effectiveness of Balancing

Both algorithms improved metrics associated with balancing. In Gekku Pedal, both spread (average distance between players) and blowout rate were far lower in the balanced condition than in the non-balanced condition. This was as expected, given that in the balancing condition, all players moved at the same speed if they were pedaling at all. In the balanced condition, the differences between players' positions were due to players stopping. Races were nonetheless close, with no blowouts seen in the balanced condition.

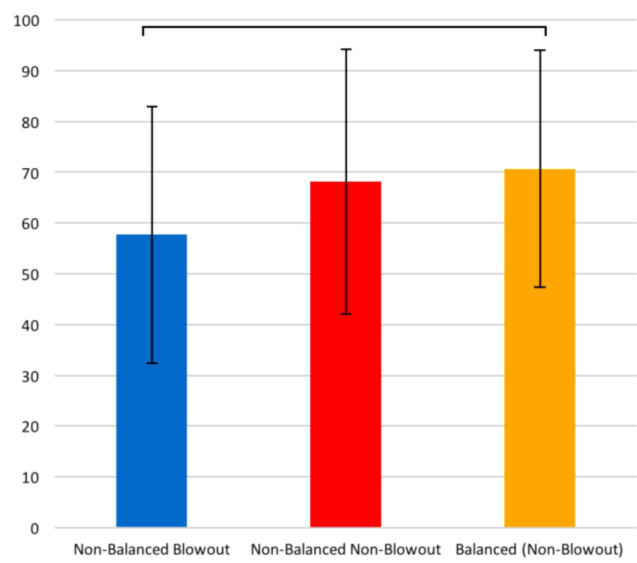

Figure 5: Average cadence in Gekku Pedal between conditions, counting blowout and non-blowout races separately in the non-balanced condition. Vertical bars show standard deviation. Horizontal hats indicate statistical significance at α = .05.

In Gekku Aim, aim assistance improved players' hit rates and final scores, indicating that the algorithm indeed improved players' ability to hit. Players with weaker aiming ability benefitted more from the balancing; this was expected, as players who miss more frequently have more opportunity for those misses to be turned into hits. The aim assistance algorithm dramatically lowered the blowout rate, indicating that players were less likely to win (or lose) by a large margin. The average spread between players decreased, but this decrease was not significant. Therefore, the primary effects of the aim assistance algorithm were to improve aiming and to reduce blowouts, although on average, races were not closer. A contributing factor is that all players saw their hit rate improve, not just those who needed it most.

RQ2: Effect on Player Behaviour and Player Perception

Two results around player behaviour are notable. First, in Gekku Pedal, <u>players expended more effort in the balanced condition</u>. These results are consistent with the observations of Jensen and Grønbæk, who also saw a positive effect of balancing on effort in exergames [13]. This result is likely because, in a less-balanced race, the weaker player is demotivated by having little chance of winning, while the stronger player sees that they can win without expending full effort. This is supported by analysis of blowout vs non-blowout races. In non-balanced blowouts, cadence was much lower than in the balanced condition, indicating that players reduced effort if the race's outcome was already clear: no need to pedal hard if you know you will win, and no need to pedal hard if won't stop you from losing.

Interestingly, non-blowouts had similar average cadence even between conditions. Motivation to exert is critical for an exergame to have any exercise value [15], suggesting an important role for balancing to maintain exergame player motivation. The possibility of winning kept players pedaling hard, whether or not pedaling quickly would actually help. This indicates that the key contribution of balancing may be to reduce the incidence of very imbalanced blowout races, and that this metric should be considered more explicitly in future research in exergame balancing.

The second notable result is that players' fire rate did not vary between conditions. This was surprising since we expected players to take advantage of aim assistance and fire more rapidly, trusting the algorithm to compensate for reduced accuracy. Players were aware that there was a difference between the balanced and non-balanced conditions, and two of eight players were particularly vocal when aim assistance was unavailable. For example, one player stated "*I'm aiming but it's not working*" in the non-aim assisted condition, referring to the increased difficulty of aiming.

The aiming problem therefore has two components: aiming itself, and time to aim. Our algorithm helped with the first, but not with the second. This example shows that it is important to understand that players may fail to adapt their play to the presence of a balancing algorithm, and that the task being balanced may have more factors than initially considered.

We expected that players would find the balanced versions of games to be more fun and more fair. Our results showed no difference in perceptions of the two conditions when all races were considered. However, analysis of blowout races in Gekku Aim did reveal differences in perception of fun and fairness. Unsurprisingly, winners of blowouts found the game more fun than losers. More interestingly, losers of blowouts found the game more fun in the balanced condition. We believe that this is because being able to hit more often makes the game fun, even when the player is devastatingly outmatched. Also, both winners and losers of blowouts found the game fairer in the balanced condition. This result is particularly surprising, but perhaps indicates that when players felt they had a better chance of landing their shots, the game felt more fair, even in the case of lopsided wins.

This result indicates that balancing can have positive benefits even in games that have poorly-balanced results. Players appear to appreciate being able to complete game tasks successfully even if they ultimately lose the game. Similar analysis of blowout races was not possible with Gekku Pedal, as there were no blowouts in the balanced condition.

RQ3: Persistence of Effects Over Time

The main contribution of this study is that we observed participants over six days of play, during which time they played the games dozens of times, and consequently came to recognize the difference between the balanced and non-balanced versions of the games. This differs from most earlier studies where play was observed over a single session.

We expected to see changes in behaviour over time as the players learned the algorithms' properties. We expected, for example, that players' effort level would drop in the balanced version of Gekku Pedal as they realized that pedaling speed did not affect avatar speed. We expected that as players came to understand Gekku Aim's aiming assistance algorithm, they would fire more frequently, allowing the algorithm to compensate for any reduced accuracy.

Surprisingly, we saw no difference in results between the beginning of the study (days 1 and 2) and the rest (days 3 through 6). In Gekku Pedal, players' exertion level remained the same over time; the difference between the balanced and non-balanced conditions did not change. All players were able to perceive that there was a difference between conditions. One commented, for example, that he felt "held back" by his lower speed in the non-balanced condition.

The fact that players did not adapt to balancing by reducing effort even after days of play is a reassuring result. Gekku Pedal uses a heavy-handed algorithm where all players move at the same speed when pedaling, and even then, players

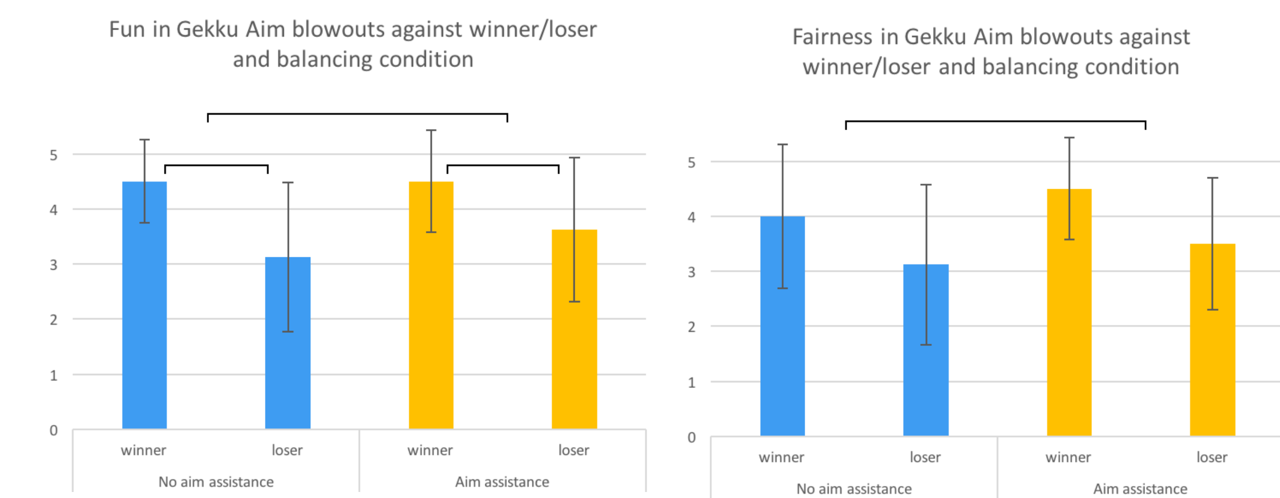

Figure 6: Fun (left) and Fairness (right) ratings in Gekku Aim for blowouts, separated by winners/losers and by presence or absence of aim assistance. Vertical bars show standard deviation. Horizontal hats indicate statistical significance at α = .05.

exerted themselves more than in the non-balancing condition, long after they understood how the algorithm worked. This lends confidence that more sophisticated balancing algorithms (e.g., heart rate balancing [21]) can be practical over the long-term.

In Gekku Aim, players did not adapt to the availability of aim assistance, as evidenced by no change in fire rate over the course of the study. Given six days to adapt to the aim assistance in Gekku Aim, players still did not take advantage of the ability to shoot more quickly while still hitting the target. This again shows that even when given the chance to observe and learn a balancing algorithm, players may continue to play as if the algorithm is not present.

IMPLICATIONS FOR DESIGN

In this section we discuss implications for design arising from this study. CP represents a difficult case for balancing due to the large differences in ability among people with CP. Conversely, game balancing represents an enormous potential benefit to people with CP, allowing them to play multiplayer games in a broader group. Further research is required but we expect our findings could also apply to motor balancing in other kinds of exergames.

Use Balancing to Enhance Player Motivation

A concern about balancing for player ability is that players will use it as a crutch instead of trying their best. This is particularly an issue in exergames, where exertion is core to the game's purpose. We found that players exerted themselves more in the balanced condition. Earlier research has found that players find close games to be more fun than unbalanced ones [6,22], and we confirm these results. Effort declined in blowout games, which occurred more often in non-balanced games. Our findings suggest that players try harder when there is a reasonable chance that either player could win, and that players continue to try harder in balanced games after extended play.

Notably, our results show that this effect persists over six days of play, indicating that the positive effects of balancing on motivation last beyond the time it takes for players to understand the presence of balancing in-game. As such, a primary goal of designers of exergames should be to use balancing mechanisms to reduce blowouts, in the expectation that players will then increase their exertion level.

Aim Assistance Should Be Visible to The Player

We found that aiming ability is comprised of two key parts: how well players can hit the target, and how quickly they can line up their shots. In our study, we made the presentation of the assistance explicit rather than hidden, but there was no clear indication of whether a shot was certain to hit. Accordingly, players could detect the presence or absence of aim assistance, but did not know whether their aim was true. Adding such an indicator (e.g., highlighting the target for a definite hit) might have encouraged players to increase their fire rate to get full advantage from aim assistance.

Prior work has shown that explicit disclosure of skill assistance does not have a significant negative impact on play experience or fairness [6,13]. Assistance should be made explicit to the players receiving the boost so that they can learn to adapt to its presence and make use of it. However, as observed by Gerling *et al.*, highly noticeable algorithms can negatively impact self-esteem [7]. This suggests that, while players must perceive balancing clearly enough to make full use of it, they should also not be able to easily tell how much or how little assistance they are receiving compared to other players.

Use Customized Balancing Algorithms

Our aiming assistance algorithm used static adjustment, providing all players with the same degree of assistance. As a consequence, all players' hit rates improved (albeit with greater improvement among weaker players – Figure 6). This approach was sufficient to cut in half the blowout rate, but not enough to reduce differences in scores. In this case, providing the same assistance to all players was not sufficient to balance the game. This result confirms the motivation for earlier research, where differing degrees of assistance are provided based on player performance.

CONCLUSION

Balancing for player ability helps people who have different physical abilities and experience levels play games together. Player balancing is particularly important in exergames where people who have different levels of physical ability, fitness, and impairment may want to play and compete together. In this paper, we investigated how players reacted and adapted to the presence of balancing in exergames over time. Our results showed that motivation was higher in balanced versus non-balanced conditions; this held even in "blowout" games where one player dominated. Furthermore, perceived fun and fairness were higher for both winners and losers in balanced versus non-balanced conditions. These results were consistent over the six days of the study, showing that the effect of balancing on players continued even after having the opportunity to understand and adapt to the algorithms. Player balancing algorithms should be designed around the multi-factored nature of ability, so that multi-player games can be engaging and fun for all players. In future research, we plan to use our findings here to implement aim assistance and GMF balancing into full games rather than focused test games. It would also be valuable to test using typically-developing youth to see if the findings of this study are generalizable.

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