Recommender Algorithms in Activity Motivating Games

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ABSTRACT

Physical activity motivating game design encourages players to perform real physical activity in order to gain virtual game rewards. Previous research into activity motivating games showed that they have the potential to motivate players to perform physical activity, while retaining the enjoyment of playing. However, it was discovered that a uniform motivating approach resulted in different levels of activity performed by players of varying gaming skills. In this work we present and evaluate two adaptive recommendation-based techniques, which aim to balance the amount of physical activity performed by players by adapting the level of motivation to their observed gaming skills. Experimental evaluation showed that the adaptive techniques not only increase the amount of activity performed and retain the enjoyment of playing, but also balance the amount of activity performed by players of varying gaming skills and allow for game difficulty to be set in a player-dependent manner.

Categories and Subject Descriptors

H.5.2 [**Information Interfaces and Presentation**]: User Interfaces, Interaction Styles, I.2.1 [**Artificial Intelligence**]: Applications and Expert Systems, Games.

General Terms: Design, experimentation, human factors.

Keywords: Recommendation algorithms, games, player adaptivity, physical activity, user study.

1. INTRODUCTION

One of the main contributors to the increasing obesity epidemic is sedentary lifestyle with an imbalanced energy consumption and expenditure. The nature of sedentary activities, like TV watching or computer game playing, is addictive and self-reinforcing. Hence, adjusting one's lifestyle by decreasing the amount of sedentary activities and increasing the amount of physical activities is not easy. We developed a new *PLAY, MATE!* design for physical activity motivating games, aimed at combating this issue in the context of computer games playing [2].

Rather than explicitly decreasing the amount of sedentary activity, the *PLAY, MATE!* design leverages the playability of games [6] to motivate players to perform physical activity while playing. The motivation is achieved by offering virtual game rewards in return for real physical activity performed. This is done by (1) modifying the game, such that certain game features are reinforced by the rewards, (2) making the players aware of the possibility of gaining the rewards in return for performing physical activity, and (3) equipping the players with external interface instantaneously capturing their activity and converting it into the rewards. We applied the *PLAY, MATE!* design to an open source game, Neverball, and motivated players to perform physical activity by offering time-based rewards. The evaluation showed that *PLAY, MATE!* motivated players to perform significantly more physical activity and did not decrease their perceived enjoyment of playing [2].

Analysis of the results raised several challenges. The first challenge referred to player dependency in the amount of physical activity performed while playing. Segmentation of players according to their gaming skills revealed that experienced players performed less activity than novice players. This motivated further research into balancing the amount of activity performed by different players and motivating all players to perform a comparable amount of activity. The second challenge referred to the variability of the perceived enjoyment of playing as a function of the game difficulty. A user questionnaire revealed that the highest enjoyment of playing is obtained when the difficulty of Neverball is adapted to player's gaming skills. This motivated further research into dynamically adapting the difficulty of game tasks to player's gaming skills.

In this work we address these two challenges using widely-used recommendation algorithms. The first is a stereotype-based *tailored reward* technique aimed at balancing the amount of physical activity performed by all players. The second is a collaborative *personalised difficulty* technique for setting personalised time limits for each player. Both techniques are purely statistical and based on previously observed interactions of players with the game. Results of a user evaluation involving *135* players showed that tailoring the rewards and personalising the game difficulty increased the amount of physical activity performed, decreased sedentary playing time, and retained the perceived enjoyment of playing. In addition, tailored reward balanced the amount of activity performed by various players, whereas setting personalised difficulty successfully shortened the time limits that were too lenient for experienced players.

Hence, the contributions of this work are two-fold. Firstly, we demonstrate two recommendation-based adaptive

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techniques for player-dependent application of *PLAY, MATE!*. Secondly, we evaluate their effect on the acceptance of *PLAY, MATE!*, as indicated by the amount of physical activity performed and the perceived enjoyment of playing. From a health perspective, the results show that the adaptive techniques increase the amount of physical activity performed while playing and help players to reach the desired degree of activity. From a gaming perspective, the results demonstrate the applicability of recommendation algorithms to the domain of computer games for an adaptive setting of player-dependent game difficulty.

The rest of this work is structured as follows. Initially, we survey related research into active computer games and personalisation in games. Then, we present the *PLAY, MATE!* design, its application to Neverball, and the use of recommendation algorithms for its adaptive application. Then, we present and analyse the results of the conducted evaluation and, finally, we conclude this work and outline future research directions.

2. RELATED WORK

Several technology-mediated persuasive solutions to the obesity problem have been investigated in the past. Lin *et al* developed a social application that links a user's physical activity to the growth and activity of a virtual fish [10]. Toscos *et al* developed a mobile application that records a user's physical activity and sends persuasive messages encouraging exercising [18]. Nawyn *et al* developed an entertainment system remote control that promotes a reduction in TV watching time and an increase in non-sedentary activities [13]. These applications aimed at changing the lifestyle of users by encouraging them to perform more physical activity. The change was mostly accepted by already motivated users and resisted by others. In contrast, the *PLAY, MATE!* design does not rely on extrinsic motivational factors, but rather leverages existing playability of games and enjoyment of playing to motivate users to perform physical activity.

Game technologies involving players' physical activity have been applied in several commercial products, like Dance-Dance Revolution[1], Wii[2], and Project Natal[3]. The first is a dance pad with arrows, on which players step to control the game. The second uses an accelerometer-equipped input device that allows players to control a game by their body motion. The third is a game controller that allows players to control a game using gestures and body motion. Despite requiring players to be active while playing, these products mainly provide bodily interfaces to interact with games rather than motivate physical activity. Their great potential – Wii sold about *50* million consoles in the first two years – has been recognised by game developers. Several works investigated practical integration of physical activity into games. Fujiki *et al* developed a racing game, in which a player's activity is captured by an accelerometer and affects the speed of the game character in a race-like interface [7]. Stanley *et al* developed a chess game, in which attacking and defending skills of the pieces depend on a player's activity captured by mobile sensors [15]. Buttussi *et al* developed two arcade games that exploit motion and physiological sensors to adjust the intensity of exercising [4]. Masuko and Hoshino developed a boxing game that exploits image processing and heart rate monitoring technologies to control the level of exercising [11]. However, these games were mainly designed as research prototypes lacking the immersion and attractiveness of commercial games, and could not be easily extended to other games. Rather than proposing new games, *PLAY, MATE!* presents a new design and gaming paradigm, which, if integrated with a variety of both existing already popular games and future games, will motivate players to perform physical activity while playing.

Although many works investigated applications of AI to computer games, very few focused on adaptivity and personalisation. Tychsen *et al* proposed to allow players to adjust their goals, appearance, and game character in order to improve player experience in online role playing games [19]. Bakkes *et al* discussed case-based modelling of artificial opponents applied to real-time strategy games and evaluated it using simulated scenarios [1]. Thue *et al* mined the observed player interactions with a game in order to determine their preferred style of playing and adapt interactive storytelling accordingly [17]. Conati and Maclaren developed a probabilistic model of player's emotions and evaluated its accuracy with real players [4]. Although these works discussed and evaluated player adaptivity in games, most of them evaluated the impact of adaptivity on player enjoyment or game playability. In addition to these, our work evaluates the impact of adaptivity on the amount of activity performed by players – a pivotal indicator of the acceptance of *PLAY, MATE!*.

3. THE *PLAY, MATE!* DESIGN AND ITS APPLICATION TO NEVERBALL

The goal of the *PLAY, MATE!* design is to change the sedentary nature of game playing to include certain aspects of physical activity. For this, the playability of games and the enjoyment of playing are leveraged to motivate players to perform physical activity in order to gain virtual game rewards. The motivation is achieved by modifying the following aspects of player's interaction with the game:

- Game motivator. Players are made aware of the possibility of gaining virtual game-related rewards in return for real physical activity performed. The game is modified in order to motivate players to perform physical activity, such that certain game features are reinforced by performing physical activity and gaining the rewards.

[1] http://www.konami.com/games/ddr/
[2] http://www.nintendo.com/wii/
[3] http://www.xbox.com/en-US/live/projectnatal/

- Activity interface. Players are provided with an external interface that instantaneously captures the physical activity performed, processes it, and converts into the game rewards.
- Game control. Since performing physical activity and controlling the game simultaneously could be over-complicated, players are provided with enhanced control over the flow of the game.

In [2], we applied *PLAY, MATE!* to an open source Neverball game[4]. In Neverball, players navigate a ball to a target point through an obstacle course and collect the required number of coins, all in a limited time (see Figure 1-left). We applied a time-based physical activity motivator: the initial time allocated to complete Neverball levels was shortened and players were made aware of the possibility of gaining extra-time in return for performing physical activity. We used a compact and lightweight tri-axial accelerometer to capture and process the activity performed [8]. The accelerometer was attached to the player's waist using a flexible band, so as not to interfere with the player's normal body motion (see Figure 1-right). The acceleration signals were transmitted to a receiver attached to the computer running Neverball. We processed the acceleration signal and discretised it into activity bursts, further referred to as *jumps* [3].

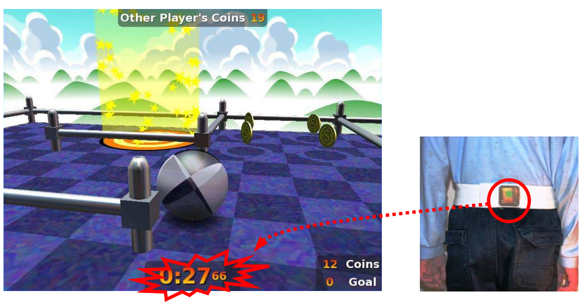

Figure 1. Accelerometer (left) and Neverball interface (right).

Players interacted with the activity motivating version of Neverball as follows. Players were motivated by a reduced time motivator and were aware of the possibility of gaining extra-time in return for performing physical activity. However, they were not instructed regarding the timing and amount of physical activity they would need to perform and this was left to their discretion. When the time remaining was perceived insufficient, players could pause the game and perform physical activity. Each jump captured by the activity interface gained extra-time to complete a level. The activity was captured by the activity interface, transmitted to Neverball, and the extra-time visualised by Neverball interface. When the remaining time was perceived sufficient, players could resume sedentary playing.

The acceptance of the *PLAY, MATE!* design was evaluated in [2] using two pivotal indicators: amount of activity performed while playing and perceived enjoyment of playing [16]. The evaluation involved *180* players aged *10* to *12*. They initially played three introductory levels of Neverball, then were equipped with the activity monitors and instructed about the possibility of gaining extra-time in return for performing physical activity, then had a *20* minute free playing session, and, finally, reflected on their perception of playing. The results showed that (1) players were successfully motivated to perform significantly more physical activity, (2) players significantly decreased their sedentary playing time and increased active time, and (3) despite realistically perceiving the amount of physical activity performed, players did not report a decrease in the perceived enjoyment of playing.

[4] http://www.neverball.org

4. ADAPTIVE APPLICATION OF *PLAY, MATE!*

Although these outcomes were encouraging, analysis of the results revealed considerable discrepancies in the amount of physical activity performed by players. It was observed that experienced players performed less physical activity than novice players: during the free playing session the former performed on average *160.9* jumps and the latter *180.6*. This result is not surprising given that experienced players naturally have higher gaming skills and better chances to complete a level without requiring the game rewards, than novice players. Hence, experienced players need the rewards to a lesser degree than novice players and perform physical activity accordingly. From a health perspective, this means that the effect of the *PLAY, MATE!* design on experienced players was weaker than on novice players.

From a gaming perspective this could be a weakness of the design, as if the game is not sufficiently challenging for experienced players, their enjoyment of playing may decrease. In fact, this is tangentially supported by another finding of [2]. While playing the introductory levels, players reported on their expected degree of enjoyment of playing, if the level time limit was modified to $k \cdot t(l_j)$, where $k=\{3/6, 4/6, \ldots, 8/6, 9/6\}$ and $t(l_j)$ is the observed completion time for level l_j. The perceived degree of enjoyment was measured on a 6-Likert scale. Table 1 summarises the average expected degree of enjoyment. As can be seen, maximal degree of enjoyment is obtained when a level time limit matches a player's observed completion time, i.e., the level difficulty is adapted to player's gaming skills. This outcome supports one of the conclusions of [16], which claimed that "*games should be designed to have a level of challenge that is appropriate [for a player] and not discouragingly hard or boringly easy*".

Table 2. Reported Enjoyment of Playing.

k	*3/6*	*4/6*	*5/6*	*6/6*	*7/6*	*8/6*	*9/6*
enjoyment	4.155	4.250	4.344	4.557	4.555	4.433	4.3667

The observed discrepancy between experienced and novice players and the maximal degree of enjoyment obtained for the matching time limit highlight the need for the development of adaptive techniques for player-dependent application of the *PLAY, MATE!* design. The following two sub-sections present the adaptive techniques we developed.

4.1 Tailored Reward

The goal of the tailored reward (*TR*) technique is to balance the amount of physical activity performed by various players. In the context of Neverball and time-based rewards, one way to achieve this is to modify the reward times gained by players. For example, reward times that experienced players gain in return for every jump can be shortened, inherently requiring them to perform more activity. Similarly, the reward times of novice players can be extended in order to retain their enjoyment of playing.

The tailored reward technique predicts a player's reward time using a stereotype-based recommendation algorithm [14]. That is, initially we determine a player's stereotype by classifying them into one of the three classes: *low, medium,* or *high*, based on their observed gaming skills. Then, we adaptively assign their reward time according to the reward time of the relevant class.

This process is divided into two stages. In the offline pre-processing stage, we divided the *180* participants, who participated in the study reported in [2], into the *low, medium,* or *high* gaming skill classes. Initially, each player played three introductory levels of Neverball. Since the conditions of playing these levels were identical for all players, the observed completion times (t_1,t_2,t_3) were used as the indicators of their gaming skills. We used these times to divide the players into the three classes. The following pseudo-code summarises the offline pre-processing stage:

Offline Pre-Processing

(1) for each player $p_i=(t_{i1},t_{i2},t_{i3})$
(2) for each player compute $gs(p_i)=\| p_i \|_2$
(3) sort all N players according to $gs(p_i)$
(4) $high=\{p_i\}$ s.t. $i=1,\dots,N/3$
(5) $ps_{high}=centroid(high)$
(6) $medium=\{p_i\}$ s.t. $i=N/3,\dots,2N/3$
(7) $ps_{medium}=centroid(medium)$
(8) $low=\{p_i\}$ s.t. $i=2N/3,\dots,N$
(9) $ps_{low}=centroid(low)$

In the pseudo-code, p_i denotes player i, $gs(p_i)$ denotes the gaming skills of p_i, $\|x\|_2$ denotes the Euclidian norm of x, N denotes the overall number of previously observed players, and *centroid()* computes the geometric centre of a set of players.

Once the offline pre-processing is completed, in the online classification stage we set the reward time for a new player p'. This is done by classifying p' into the most appropriate class *{low, medium, high}* and assigning the reward time of the class to p'. The following pseudo-code summarises the online classification and setting the reward time stage:

Online Setting of the Reward Time for p'

(1) $class(p')=argmin_{x=\{low,medium,high\}} \| p'-centroid(x) \|_2$
(2) $reward(p')=reward(class(p'))$

It should be noted that a player's reward time is not truly personalised, but rather stereotypically tailored to the skill class, into which a player is classified.

4.2 Personalised Difficulty

The goal of the personalised difficulty (*PD*) technique is to set the difficulty of a game level in a player-dependent manner, such that it motivates players to increase the amount of physical activity performed, while retaining (and possibly increasing) the enjoyment of playing. In the context of Neverball, when the time allocated to complete a levels is shortened, the new time limit of should become challenging to motivate players to perform physical activity, but neither too short (to discourage players) nor too long (to bore players).

The personalised difficulty technique predicts a player's completion time for a level using collaborative filtering-based recommendation algorithm [9]. That is, initially we compute player-to-player similarity degree using the completion times observed for previously played levels. Then, we select a subset of most similar players. Finally, we aggregate the completion times of the most similar players for the target level, in order to predict the completion time of the target player.

The personalised difficulty technique is implemented as follows. For each player p_i and each completed level l_j, we capture the level completion time[5] $t(p_i,l_j)$. We use the observed completion times to adaptively predict the completion time $t'(p_x,l_y)$ for the target level l_y that will be played by the target player p_x, and shorten the level time limit accordingly. The degree of similarity $sim(p_x,p_i)$ between p_x and every other player p_i is computed using the completion times (t_1,t_2,t_3) observed for the three introductory levels and the times observed for already completed levels $l_1,l_2,\dots,l_{y-1}$ of the free playing session. After selecting the neighbours, i.e., set of players most similar to p_x, the predicted completion time $t'(p_x,l_y)$ is computed by aggregating the observed completion times $t(p_i,l_y)$ of the neighbours in a weighted manner, according to their player-to-player similarity degree $sim(p_x,p_i)$. Finally, the time limit for player p_x and level l_y is set to the predicted completion time $t'(p_x,l_y)$.

It should be noted that unlike the tailored reward time, the personalised difficulty uses truly *personalised* recommendation algorithm, as both the similarity of players and the predicted completion times are computed on an individual basis.

[5] Here we refer only to the sedentary playing time, i.e., the time player directly interacted with the game, and disregard the time spent on performing physical activity.

5. EVALUATION

5.1 Experimental Setting

We evaluated the impact of the adaptive application of the PLAY, MATE! design on the amount of physical activity performed and perceived enjoyment of playing. Players already familiar with Neverball or having any medical limitations preventing them from performing mild physical activity were excluded from the evaluation. *135* players participated in the evaluation. Similar to the experiments reported in [2], players first played the three introductory levels of Neverball, then were instructed about gaining extra-time in return for performing physical activity, then had the *20* minute playing session, and, finally, reflected on their perception of the playing.

135 participants from two primary schools in the Hobart (Australia) area participated in the evaluation. We presumed that Neverball is appropriate for players aged *10* and *12* and recruited accordingly: *48* were *10* years old, *51* were *11* years old, and *36* were *12* years old. *68* players were boys and *67* were girls. The *135* participants were randomly split into three groups of *45* players in each. The first group (referred to as *UT*) played non-adaptive activity motivating version of Neverball. That is, level times were shortened in a *uniform* manner for all players and for every jump players gained *1* second of time reward.

The second group (referred to as *UT+TR*) played adaptive activity motivating version of Neverball with *uniform time and tailored rewards*. After playing the introductory levels, each player was classified into the *low*, *medium*, or *high* skill class as detailed in previous section, and player's reward time for every jump captured was set accordingly. In the evaluation, we applied *reward(high)=0.78*, *reward(medium)=1*, and *reward(low)=1.38* seconds[6]. Level time limits in this group were set in a uniform manner for all players, similar to the *UT* group.

The third group (referred to as *UT+PD*) played adaptive activity motivating version of Neverball with uniform *time and personalised difficulty* of levels. Time limits for each player and level were computed as detailed in previous section. We used Pearson's correlation to compute player-to-player similarity degree and aggregated the observed completion times of *5* neighbours to predict the completion time. Reward times in this group were set in a uniform manner for all players, similar to the *UT* group: for every jump players gained *1* extra second.

As the tailored reward and personalised difficulty adaptive techniques aimed at achieving different goals, i.e., balanced amount of activity versus player-dependent game difficulty, no group evaluating their combined effect was included in the evaluation.

[6] These reward times are based on analysis of previously observed players. Due to space limitations the details of the analysis are omitted.

5.2 Overall Acceptance of Player Adaptivity

Two pivotal indicators of the acceptance of the PLAY, MATE! design are the amount of physical activity performed while playing (quantified by the number of jumps captured and time distribution between the sedentary playing and performing physical activity) and the perceived enjoyment of playing (measured on a 6-Likert scale). The former shows the extent to which players are actually motivated to perform physical activity, while the latter shows whether, despite performing the activity, they still find the game enjoyable.

Table 2 summarises the obtained results. As can be seen, both the adaptive techniques successfully increased the overall amount of physical activity performed. The average number of jumps captured during the *20* minute free playing session increased from *255.40* in the *UT* group to *270.96* in the *UT+TR* group and *297.67* in the *UT+PD* group. The difference was statistically significant for the *UT+PD* group ($p<0.05$) and not significant for the *UT+TR* group[7]. To strengthen this, we measured the distribution between sedentary playing time t_{sed} and physical activity time t_{act}, as observed during the *20* minute free playing session. The relative active time t_{act} increased from *23.99%* in the *UT* group to *24.12%* in the *UT+TR* group and *25.81%* in the *UT+PD* group. The difference was statistically significant for the *UT+PD* group ($p<0.05$) and not significant for the *UT+TR* group.

Table 2. Acceptance of Adaptive Application of PLAY, MATE!.

	UT	*UT+TR*	*UT+PD*
number of jumps captured	255.40	270.96	297.67
relative sedentary time t_{sed}	76.01%	75.88%	74.19%
relative active time t_{act}	23.99%	24.12%	25.81%
enjoyment of playing	5.467	5.378	5.556

The impact of adaptivity on the perceived enjoyment of playing is mixed. On one hand, performing physical activity while playing interrupts the flow of playing, which could potentially decrease the enjoyment. On the other hand, player interaction with the game is player-dependent and adapted to their gaming skills, which could potentially increase the enjoyment. Comparing to the *UT* group, the enjoyment of playing decreased in the *UT+TR* group and increased in the *UT+PD* group. That is, additional physical activity decreased the enjoyment in the *UT+TR* group, but the difficulty adaptation in the *UT+PD* group outweighed this decrease and the perceived enjoyment increased. It should be mentioned that both the decrease and increase of the perceived enjoyment were not statistically significant. Hence, both the adaptive techniques retained the perceived enjoyment of playing.

In summary, the adaptive techniques increased the amount of physical activity performed by players both in terms of the number of jumps captured and relative active time (not significant for the *UT+TR* group, but significant for the

[7] All statistical significance results hereafter refer to a two-tailed t-test assuming equal variances.

UT+PD group), while retained the perceived enjoyment of playing.

5.3 Tailored Reward

The goal of the tailored reward technique was to balance the amount of activity performed by players of varying gaming skills. To evaluate the impact of this technique, we classified the players into *low*, *medium*, or *high* classes based on to the completion times (t_1,t_2,t_3) observed for the three introductory levels of Neverball, set the reward times accordingly, and compared the average amount of activity performed by players in each class during the *20* minute free playing session. Figure 2 summarises the average number of jumps captured for each class in the *UT* and *UT+TR* groups.

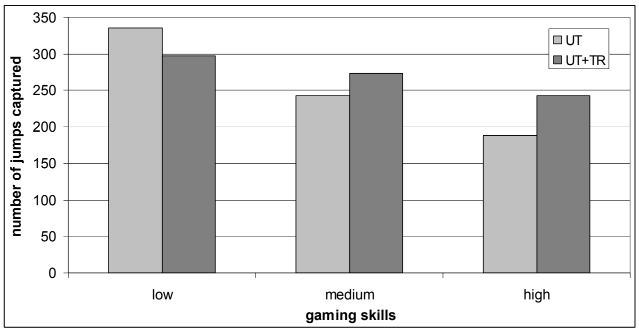

Figure 2. Effect of Tailored Rewards on Physical Activity.

The overall trend in the skill classes remained unchanged: high-skilled players performed less physical activity as they need the reward times to a lesser degree than low-skilled players. Although applying the tailored reward technique did not equalise the number of jumps across the three skill classes, it balanced them to a certain extent and substantially diminished the differences between the classes. The number of jumps decreased from *335.33* to *297.20* in the *low* class and increased from *188.27* to *242.33* in the *high* class. The decrease in the *low* class was not statistically significant, while the increase in the *high* class was statistically significant, $p<0.05$. Overall, the ratio between the numbers of jumps captured in the *low* and *high* classes dropped from *1.78* in the *UT* group to *1.23* in the *UT+TR* group.

In summary, the tailored reward technique was an important step towards balancing the amount of physical activity performed and motivating all players to perform a comparable amount of physical activity. As a result of applying this technique, experienced players performed significantly more activity and novice players performed less activity. From a health perspective, the tailored rewards techniques balanced the amount of physical activity performed and helped players to reach the desired degree of activity. From a gaming perspective, it demonstrated that the virtual rewards in the *PLAY, MATE!* design can be practically set in an adaptive player-dependent manner.

5.4 Personalised Difficulty

The goal of the personalised difficulty technique was to set level difficulty, i.e., the time limit, in a player-dependent manner, in order to motivate players to increase the amount of physical activity performed, while retaining (and possibly increasing) the enjoyment of playing. To evaluate the impact of this technique, we first ascertain the accuracy of the completion time predictions. For this, we use the NMAE predictive accuracy metric [9], computed by:

$$NMAE(l_y) = \frac{\sum_{i=1}^{N_j} \left| t(p_x,l_y) - t'(p_x,l_y) \right|}{N_y \; t'(l_y)} \qquad (1)$$

where $t'(p_x,l_y)$ is the predicted and $t(p_x,l_y)$ is the observed completion time for target player p_x and level l_y, N_y is the number of players who completed level l_y, and $t'(l_y)$ is the uniform completion time for level l_y set for the *UT* group.

Table 3 summarises the NMAE scores computed for participants in the *UT+PD* group for the first *10* levels of Neverball (for other levels, the number of players was insufficient). As can be seen, NMAE generally decreased with the number of levels completed[8]. This aligns with prior collaborative filtering research, which showed that the accuracy of the predictions improves with the amount of information about users [9]. The average prediction error across all *10* levels was *29.42* seconds in the *UT* group and *25.40* seconds in the *UT+PD* group. The difference between the groups was statistically significant, $p<0.05$.

Table 3. NMAE of Predicted Level Completion Times, *UT+PD*.

l_y	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
$NMAE(l_y)$	0.35	0.73	0.72	0.60	0.54	0.38	0.19	0.26	0.13	0.20

To assess the correlation between the predicted completion time and the amount of activity performed, we also computed the error between predicted completion time $t'(p_x,l_y)$ and the observed completion time $t(p_x,l_y)$. In this case, we were interested in the exact rather than absolute value of the error. If the observed completion time is shorter than predicted, a player has spare time and does not need to perform physical activity. If the observed completion time is longer than predicted, a player needs to perform physical activity in order to gain the reward extra-time. In this case, we do not normalise the error, as the errors are not compared across different levels. Hence, we used the MAE metric [9], computed by:

$$MAE(l_y) = \frac{\sum_{i=1}^{N_j} t(p_x,l_y) - t'(p_x,l_y)}{N_y} \qquad (2)$$

Figure 3 depicts MAE and the average number of jumps captured for the first *10* levels of Neverball in the *UT* and *UT+PD* groups. The horizontal axis represents the levels and the vertical axis represents both the number of jumps captured (left scale for the 'number of jumps captured' bars) and the time prediction error $MAE(l_y)$ (right scale for the

[8] Due to the low difficulty of l_1, the observed completion times were uniform across most players and predicted completion times were highly accurate.

'time prediction error' curves). Light bars represent the *UT* group and dark represent the *UT+PD* group.

A comparison of the two MAE curves clearly shows that the personalised time limits in the *UT+PD* group were more accurate than the uniform time limits in the *UT* group. For example, the highest average error of the personalised time limits in the *UT+PD* group was about *5.5* seconds (for l_4, l_7, and l_{10}), whereas the average error of the uniform time limits in the *UT* group was considerably higher (*32.4* seconds for l_3, *53.5* seconds for l_7, and *27.1* seconds for l_5).

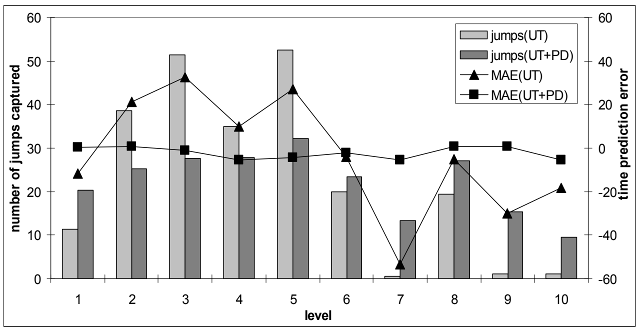

Figure 3. Effect of Personalised Difficulty on Physical Activity.

Two types of levels need to be distinguished. For l_2, l_3, l_4, and l_5, the MAE scores in the *UT* group were positive. That is, the observed completion times were longer than the uniform completion time, i.e., the time limit was too *tight* and insufficient to complete these levels. Hence, players needed to perform physical activity in order to gain the reward time. In contrast, for l_1, l_6, l_7, l_8, l_9, and l_{10}, the MAE scores in the *UT* group were negative. That is, the observed completion times were shorter than the uniform completion time, i.e., the time limit was too *lenient*. Hence, players had some time remaining when completed these levels and did not need to perform any physical activity. In the *UT+PR* group, the MAE values fluctuated around *0*, as the time limit is adapted to player's gaming skills. The difference between the groups was statistically significant, $p<0.01$. Hence, personalised completion times predicted for players in the *UT+PR* group were significantly more accurate than the uniform times in the *UT* group.

Considering the correlation between the adaptively predicted level time limits and amount of physical activity performed, the impact of player-dependent time limit was mixed. For l_2, l_3, l_4, and l_5, adapting the time limit in the *UT+PD* group *extended* the tight time limit. Hence, players needed to gain less reward time, performed less physical activity, and the number of jumps captured decreased. For l_1, l_6, l_7, l_8, l_9, and l_{10}, adapting the time limit in the *UT+PD* group *shortened* the time limit. Hence, players needed to gain more reward time, performed more physical activity, and the number of jumps captured increased. Both the decrease (l_2, l_3, l_4, and l_5) and increase (l_1, l_6, l_7, l_8, l_9, and l_{10}) in the number of jumps were statistically significant: $p<0.01$ for the decrease and $p<0.05$ for the increase.

In summary, the personalised difficulty technique allowed us to adaptively control the difficulty of Neverball levels by setting player-dependent time limits. From a health perspective, the impact was mixed: for some levels the amount of physical activity performed increased, but for some decreased, in both cases significantly. That is, if aimed at maximising the amount of activity performed while playing, the personalised difficulty technique should be applied selectively. It should be applied to easy tasks to make them harder, but should not be applied to sufficiently difficult tasks not to make them easier and decrease the amount of activity performed by players. From a gaming perspective, this technique retained (and even slightly, although not significantly) increased the perceived enjoyment of playing.

These outcomes exemplify the applicability of adaptive techniques and recommendation algorithms to computer games and demonstrate their potential to increase the perceived enjoyment of playing.

6. CONCLUSIONS AND FUTURE WORK

This work was motivated by previous research into the *PLAY, MATE!* design for physical activity motivating games. These games leverage the playfulness of games and the enjoyment of playing in order to motivate players to perform physical activity while playing. *PLAY, MATE!* was applied to the Neverball game and user evaluation showed that players were motivated to perform more physical activity and did not decrease their enjoyment of playing. However, the amount of physical activity performed and the enjoyment of playing were player-dependent.

To address this, we developed two adaptive techniques based on widely-used recommendation algorithms, which were aimed at balancing the amount of activity performed and retaining the enjoyment of playing. We evaluated the adaptive techniques in a study involving *135* players aged *10* to *12*. Analyses of the results showed that the adaptive techniques (1) increased the amount of physical activity performed by players, (2) changed the distribution between sedentary and active time, (3) retained the perceived enjoyment of playing, and (4) should have been applied selectively, in order to increase the difficulty of easy tasks and not to decrease the difficulty of already difficult tasks.

The implications of these findings are two-fold. From a health perspective they demonstrate that adaptive player-dependent techniques have the potential to increase the amount of activity performed while playing physical activity motivating games. From a gaming perspective they exemplify the applicability of recommendation algorithms to computer games and demonstrate that adapting game difficulty to player's gaming skills can potentially increase the perceived enjoyment of playing.

In the future, we plan to investigate game- and player-dependent conversion of physical activity into game rewards. For example, in Neverball we applied time-based game rewards, whereas in strategy games physical activity should be converted into game resources. Alternatively, in role playing games players can be portrayed by different character and the rewards should be tailored to the selected character. Moreover, physical activity can possibly improve several resources or skills of the game character. We intend to develop game- and player-dependent user modelling and personalisation techniques, which will monitor player's strategy and interactions with the game and adapt the rewards accordingly.

Physical activity motivating games are designed to motivate players to perform physical activity while playing. As the evaluation showed, the amount of physical activity performed is player-dependent. However, both a player's fitness level and gaming skill change over time. We will investigate ways of monitoring these two parameters and adaptively increasing the amount of physical activity players perform, while preserving the game challenge and the enjoyment of playing.

Finally, we plan to conduct a longitudinal study, in which players will interact with a suite of activity motivating games in their natural playing environment, e.g., at home, for an extensive period of time. The outcomes of the longitudinal study will assess whether the *PLAY, MATE!* design actually leads to the desired long-term behavioural change, and essentially to a healthier lifestyle, offering an alternative way to combat the obesity problem.

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