Difficulty Pacing Impact on Player Motivation

William Rao Fernandes[0000−0001−9378−0074] and Guillaume Levieux[0000−0001−8844−4447]

Conservatoire National des Arts et Metiers
CEDRIC
first.last@cnam.fr

Abstract. Challenge, and thus difficulty, is one of the main factors of enjoyment and motivation in video games. To enhance the players' motivation, many studies rely on Dynamic Difficulty Adjustment model in order to follow a difficulty curve. However, few authors worked on the shape of the difficulty curve itself. Our goal in this paper is to evaluate how players react to different difficulty curves. We use four different difficulty curves, including two flat curves and two curves with different baseline and peak levels. We test those curves on 67 students of a video games school while playing a First-Person Shooter game. Our study shows that curves with peaks have the strongest impact on players' motivation.

1 Introduction

Whether when studying video games or psychology, motivation is an important part of the literature. In fact, many studies on video games are using psychology theories in order to enhance the players' motivation [29][20][8][19]. Many of these studies try to design a difficulty curve that matches the Flow Theory, as the flow state is known as a mental state where players are strongly focused[27]. This is considered as an engaging moment, providing a positive feeling between arousal and control. The flow theory states that difficulty should be neither too hard nor too easy, matching the player skills, and that other interesting states can be obtained by slightly unbalancing difficulty. However, there are no scientific studies on what kind of difficulty curve might enhance the players' motivation even more. The only articles we found are from game designers who share their point of view about their industrial experiences[34][31][11].

The goal of this paper is to design different difficulty curves in order to enhance the players' motivation. Then, by using these curves in a video game, compare the players' actual motivation for each curve. To do so, we will use a Dynamic Difficulty Adjustment (DDA) model which can follow any difficulty curve [28].

The paper starts with a literature review of difficulty and motivation, which help us shape our DDA model. However, few authors have experimentally studied difficulty curves shapes, but there exists theoretical models and design good practices that can help us to design our difficulty curves and to form our hypotheses. Then we detail our experiment, present our results and finally discuss them.

2 Difficulty and Motivation

Many authors consider challenge as one of the core features of video games' enjoyment. Ryan et al. study intrinsic motivation and apply Self-Determination Theory to video games. They show how enjoyment is related to the feeling of competence, which relies on an optimal level of challenge, and thus, on the game's difficulty [29]. Jesper Juul's definition of video games states that a video game has quantifiable outcomes, influenced by the players' effort. This definition puts challenge as part of the very nature of a game, as the level of challenge mainly drives the effort the players have to put in the game. Juul also provided insight on how failure, and thus difficulty, is one of the core aspects of video game enjoyment and learning progression [17][18]. Malone considers that video games are captivating because they provide challenge, foster the player's curiosity and propose a rich fantasy[25]. Malone explains that challenge is directly related to the game's difficulty and corresponds to the uncertainty for the players to reach the game's goals. Lazzaro proposes a four factor model, where *Hard Fun* is related to the feeling of overcoming difficult tasks [20]. Sweetser et al. see also challenge as one of the most fundamental part of their Game Flow framework [32].

The work of Sweetser et al. stems from Mihaly Csikszentmihalyi's Theory of Flow [27], who has been trying to figure out the properties of activities showing a strong, intrinsic ability to motivate. Csikszentmihalyi research states that these activities provide *perceived challenges, or opportunities for action, that stretch (neither over matching nor underutilizing) existing skills* [27]. Such a flow state has been shown to be globally amplified by the use of a basic difficulty adjustment system [3]. A study of large population of players in two commercial games confirm that players prefer specific levels of difficulty[1].

In order to enhance the motivation of the player, many studies focused on Dynamic Difficulty Adjustment (DDA) models. DDA models are used to automatically change the difficulty parameters of a game, based on the players' skills, in order to keep the players entertained. Many DDA models are using data representing the player's performance. The +/- δ algorithm, for instance, can start with no data and only use the player's last success or failure to converge to what we may call a *balanced* difficulty state, where the player has a 0.5 probability to fail [28]. Constant used this algorithm to adapt the difficulty of three games based on logical, motor and sensory difficulties [8]. This algorithm is also used in the famous game Crash Bandicoot[12]. DDA algorithms can be specific to a game genre, like the Rubber Band artificial intelligence (AI), used for sport or racing games, that will adjust the difficulty by comparing the position of the enemies and the player[37]. We also have more advanced models, using learning algorithms to adapt the difficulty like Andrade with Q-learning[2], dynamic scripting[30], or Monte Carlo Tree Search[14][9][16]. In a previous research, we developed a simple DDA algorithm that needs few data points[28]. The model is using both +/- δ algorithm and logistic regression. The +/- δ algorithm is used to gather enough data until the logistic regression is accurate enough, which let the model estimate the parameters needed to provide the targeted failure probability.

Difficulty is thus a fundamental aspect of video games, and the progression of difficulty seems to be one of the many ways that video games can keep us motivated and concentrated for long period of times. One way to enhance motivation using difficulty is by designing difficulty curves that represent how difficulty will change over time. By shaping the difficulty curve, designers can decide when to challenge the players, when to give them rest, gradually increasing or decreasing difficulty or creating difficulty peaks. The difficulty curves can also be used by a DDA model, as presented previously. However, there is little to none literature about how to design a good difficulty curve. We thus focus on the difficulty curve's shape, in order to provide experimental evidence of their impact on player's motivation.

3 Difficulty Curves

As we said, difficulty is thought over time. Games rarely have the same difficulty level from the beginning to the end[1]. One way to plan the pace of difficulty is to design a difficulty curve that will drive the game's difficulty during the game session [6]. According to some game designer and also proposed by [21], a good difficulty curve will start low in difficulty, gradually raising the difficulty until a specific event occurs. Then, difficulty can be lowered to let the players enjoy their success, and then gradually increase again to repeat the pattern [34][31][11]. Often, the difficulty curve will match the introduction of new gameplay mechanics that the player will have to master in order to move forward. That is the case for The Legend of Zelda, an iconic game from Nintendo[26]. The players will get a new item at the beginning of a dungeon, meaning that they will need to learn new skills. This leads to a difficulty peak. Then, as the players explore the dungeon, they will improve their skills, which translate to the difficulty going down. Finally, the players will face the dungeon master, a new peak of difficulty. Getting out of the dungeon, the new item will allow players to reach new parts of the game map, that were not accessible, or unlock shortcuts, and difficulty is thus going down. But these new parts of the game maps may lead to stronger enemies, new dungeons, and thus the difficulty goes up again.

Allart et al. worked on the impact of two games difficulty curves on player retention. The data comes from two industrial games, Rayman Legends and Tom Clancy's: The Division [1]. They showed that difficulty is by itself an explanatory variable of player retention, and that players tend to prefer higher levels of difficulty. It is to note that both games have almost always a probability of failure under the balanced difficulty of 50%. They have also shown that people prefer lower difficulty at the beginning, which confirm the self-efficacy theory[5]. This paper also shows that difficulty peaks are present in Ubisoft games[1]. It is shown that players enjoy difficulty peaks when the game is not punitive like Rayman Legends, which comforted us for our experimentation, as difficulty curves and difficulty peaks seemed at least as important as overall difficulty.

Loftus studied why gamers are attracted to video games [23]. At this time, players mainly played paying arcade games. Players were rewarded by a high score when playing well, and had to pay when losing in order to keep their progression. The main goal of game designers was to have a difficulty hard enough, so the players lose a lot, but they feel like they can beat the game, so they keep playing. The path to success is reachable but close to failure, and the players might regret their decisions afterward[13]. Regret is a way to make the players try again where they failed, because they were close to the success they wanted. To apply that idea of regret, we can use difficulty curves with some peaks of difficulty. By doing so, we challenge the players to higher difficulty than they are used to, which lead to a greater reward when they clear the level.

Weiner described that people react with positive emotions if they feel like their actions are the cause of success [35]. However, Weiner showed that people will feel less positive emotions if the task is too easy, which confirms that the task difficulty is a variable we need to take into account. We can apply that to video games, as the players will feel less satisfied winning a game if they know that the game difficulty was set to easy[24]. Klimmt decided to let the players know in which difficulty they were during his experimentation. However, Klimmt found out that players enjoyed the game more with a lower difficulty, when they had very few failures[19]. It is to note that players had 10 minutes of gameplay, which leads us to suggest that the first contact with the game should be with a low difficulty. The idea of positive emotion linked to success is also found in a more advance form of the Flow theory, where the authors seek to propose tasks with a difficulty lower than the people skills in order to put people in different positive emotional states[27].

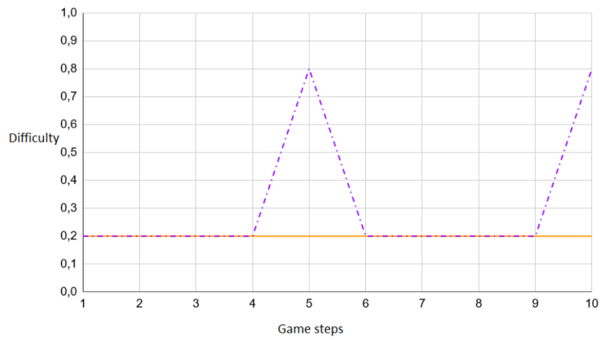
Linehan et al. focused on four mainstream puzzle games, Portal, Portal 2, Braid and Lemmings. They analyzed the data from these games in order to understand why people were attracted to them. For all the games, the same pattern is used. The beginning of the game is really simple, as players need to learn the basic mechanics. Then each time the game includes a new mechanics, they have some time to familiarize with it with a low difficulty puzzle before getting to a more challenging level of difficulty[22].

Following our literature review, we have three major point to design a difficulty curve. The first one is the starting difficulty. Following Linehan et al., as well as Bandura's self-efficacy theory, each of our curves will start low[5][22].

The second point is the difficulty level. We can follow the flow and suggest a curve that goes up to 50% chance of winning because, as we saw it in the literature review of difficulty and motivation, it is widespread. This will be our balanced curve that we will name *Flow* Curve as it simply follows the goal of matching the player skills. To test the difference with difficulty level, we designed an 80% chance of winning curve, as players might prefer a lower difficulty[19]. This will be our*Low* Curve.

The third point is the presence or absence of difficulty peaks. We found in the literature review of the difficulty curves that making difficulty peaks is pleasing for the players[34][31][11]. We designed two more difficulty curves, with the same baseline as the first two, but adding high difficulty peaks that reach 80% chances of failure. We thus add the *Low Peaks* and the *Flow Peaks* curves.

Figure 1 shows the shape of each of the curves we designed for the experiment.



(a) *Low* difficulty curves.

(b) *High* difficulty curves.

Fig. 1. Designed difficulty curves
The continuous orange curves are flat curves, while the dotted violet ones are curves with difficulty peaks. Difficulty peaks appear at every five rounds of the game, with a failure probability of 0.8.

4 Experimentation

4.1 Hypotheses

Lomas et al study leads us to suppose that the game difficulty can lead players to a lack of motivation if they know they are playing on low difficulty [24]. We thus chose not to explicitly show the current game's difficulty. Then we start following the root of the flow theory, with a difficulty that matches the player's skills. This is however contradictory with Klimmt et al study, that shows that player might prefer lower difficulty as they provide more positive feedbacks, [19]. The first hypothesis that we will put to test will thus be that the Flow curve, which offers a difficulty corresponding to the player's skill, might be more appreciated than the Low curve.

We are using a game that is not punitive. We will present the game in the Methodology section. In this game, losing leads the players to another try at a similar task, the only difference between the failed task and the new one will be the task difficulty. The players will face the same enemy, in the same arena, with the same items. In this context, following [1] discussion, we believe that the difficulty curves with peaks will be more appreciated, because they will bring more satisfaction if the player succeeds when the difficulty is high, but they will feel very little frustration if they fail, because they can directly start playing again without loss of progress.

Finally, our last hypothesis is the grouping of the first two other hypotheses, which is that the Flow Peaks curve will be the most appreciated of the four curves.

1. The Flow curve is more appreciated than the Low curve;
2. The curves with peaks are more appreciated;
3. The Flow Peaks curve is more appreciated than the others.

4.2 Methodology

In this paper and following Levieux and Aponte et al., we consider that an estimation of the game's difficulty is very close to the estimation of players' performance, that we define as their failure probability[21, 4]. As shown in Figure 1, the curves represent the failure probability at each try.

We modified a Unity First-Person Shooter (FPS) mini-game to make it a one versus one arena game[33]. The Figure 2 is a screenshot during a play session. In this game, the player can move forward, backward, left and right, and can move the camera using the mouse. We only used one type of weapon, in order to reduce the variability for this experiment. We modified the level design and enemy AI so that the player will fight in an arena versus an AI-controlled enemy. The AI will patrol the map and, when it sees the player, will start to follow them and shoot them. Each time the player beats the enemy, a new enemy respawns, and we refill the player's health. If the player dies, we destroy the enemy, then respawn the player and a new enemy. The AI has different parameters that change according to the difficulty. We can change its movement speed, shooting speed, shooting range, and player detection range.

We use a DDA model developed in a previous research to follow our difficulty curve [28]. This DDA model allows us to follow any difficulty curve using as few data points as possible. It can be used on many game types, allows a developer to set the game's difficulty to any level within approximately two minutes of playtime. In order to roughly estimate the difficulty as quickly as possible, the model drives a single metavariable to adjust the game's difficulty. As described, the game difficulty depend on the game's variables which are the enemy moving speed, shooting speed, shooting range and detection range. It starts with a simple $+/-\delta$ algorithm to gather a few data points, and then uses logistic regression to estimate the players' failure probability when the smallest required amount of data has been collected.

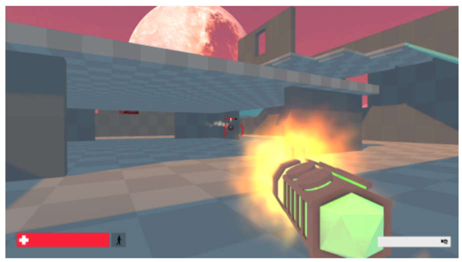


Fig. 2. Game Screenshot. The player is aiming the enemy

The experience has three phases. The first one is a questionnaire about the player's gaming habits and self-efficacy profile. This questionnaire has been used in an experimentation on Players' confidence [7], but we removed the last part on risk aversion. It is to note that this questionnaire is in French, as our participants are all French-speaking people.

The second part is the game session. Participants will have to play for at least 10 minutes and up to 20 minutes. At the start of the session, we pick a random difficulty curve between our four curves. During the game session, the player will face an AI-controlled enemy in an arena fight. When 5 minutes pass, a button appears on the top right of the screen, asking if the player is bored. If the player clicks on it, the game will select another difficulty curve. After 5 more minutes from the click, the button will reappear. Clicking again on the button will end the game session. We brief the players before the game session about the button, so they cannot miss it while playing. By doing this, we want to register a playtime, and consider that the playtime is a way to indirectly evaluate the players' motivation.

No matter how the game session ended, by clicking the buttons or by playing 20 minutes, the player will enter the third phase of the test, and fill is the Game Experience Questionnaire or GEQ [15] that has been translated into French. The experimentation sessions took place at LeCNAM ENJMIN, a video game school[10]. Most students there play video games and use 3D software, so our participants already know how to navigate a 3D world and play a FPS with a PC setup. Indeed, learning these skills on a 20 minutes game session would not be representative of a real play session.

5 Results

Sixty-seven participants played our shooter game (55 male and 12 female) with a mean age of 23 ($\sigma = 3.24$). Participants played for at least 10 minutes, and up to 20 minutes, with a mean playtime of 17 minutes and 40 seconds.

We estimate the DDA model's quality for each participant. To do so, we calculate the ratio of the number of prediction errors to the total number of predictions for each play session. We decided to remove extreme values, using the interquartile range (IQR) of the statistical dispersion of the model's quality[1] We removed 8 participants with a too high prediction error ratio. We checked the players' performance by calculating the mean difficulty of their tries, in order to detect if some players did not understand the rules of the game, or on the contrary, if they found an exploit that would lead them to victory at each try. But we did not find any abnormal data.

We have three hypotheses to test, using the data we collected. Our first hypothesis concerns the baseline difficulty of the curves. We are thinking that participants will enjoy the game more with a higher difficulty level, that will put them in the flow state or arousal state. Those two states should motivate the players or at least make them play longer, which means that we expect participants to play longer on the Flow curve and Flow Peaks curve.

Our second hypothesis, following the literature, is that participants played longer on curves with difficulty peaks. We also expect participants to play longer on high difficulty curves, and on difficulty curves with peaks. Combining these two statements, we expect the Flow Peaks curve to be the more appealing curve of all four.

In order to check our hypotheses, we checked for each participant how long they played on the first curve, before clicking on the button for the first time. Because the player could click on a button to tell us when they are getting bored, we use the playtime as an estimation of the player enjoyment of the game for this curve. As shown by Figure 3, most of the participants who had the Flow curve played less, meaning they pressed the button earlier, while participants with Low, Low Peaks and Flow Peaks curves played longer before pressing the button.

To validate that visual data, we did several Wilcoxon Rank Sum tests, each time testing a specific curve's playtime versus the three others[36]. As we can see on figure 2, we got significant results while testing the Flow versus the Flow Peaks curve, which partially validate our hypothesis that players prefer difficulty curves with peaks. However, we don't have the same results with the Low curve versus the Low Peaks curve. To further test our hypothesis regarding curves with peaks versus flat curves, and high difficulty curves versus low difficulty curves, we compared the participants' playtime on the different curves, grouping the data two by two. The first one are Low difficulty curves and High difficulty curves, but as we can see on Figure 3, the graphical result is not as we expected.

[1] To find the extreme value, we get the upper extremity of the dispersion: Quartile 3 + 1,5*IQR.

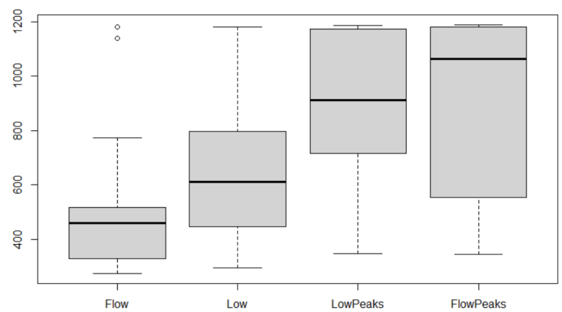


Fig. 3. Playtime of the participants on the first curve chosen

We did a Wilcoxon Rank Sum test to check if the high difficulty versus low difficulty had some significant results, but they were not with a p-value of 0.16, which means our hypothesis on the game being more appealing when the difficulty is higher is wrong. We will discuss this result in the next section.

	Low	Low Peaks	Flow
Low Peaks	0.07	X	X
Flow	0.1	0.03*	X
Flow Peaks	0.06	0.8	0.008**

Table 1. P-value of the Wilcoxon Rank Sum tests comparing the playtime for each couples of curves. The Flow Curve is significantly lower than the two curves with peaks, no matter the overall difficulty. * for $p < 0.05$, ** for $p < 0.01$

The second comparison was between curves with peaks and flat curves, which is our second hypothesis. Players seem to play longer on the curves with peaks, as seen in Figure 4, supporting our hypothesis.

To fully validate this hypothesis, we made another Wilcoxon Rank Sum test using for each curve the playtime data and grouping the flat curves together and the curves with peaks together, with p-value ≈ 0.003, rejecting the null hypothesis and thus supports us with our hypothesis.

To sum up, our results do not validate our hypothesis for the high difficulty. However, Flow Peaks and Low Peaks are the two curves with the longest playtime, and the data validate our hypothesis that people will prefer curves with peaks. In addition, Flow Peaks curve is the one with the longest playtime. However, we cannot affirm that the Flow Peaks curve is the most appealing of the four curves. It is to note that we were wrong saying that the Flow Curve would be more appealing than both the Low and Low Peaks curve.

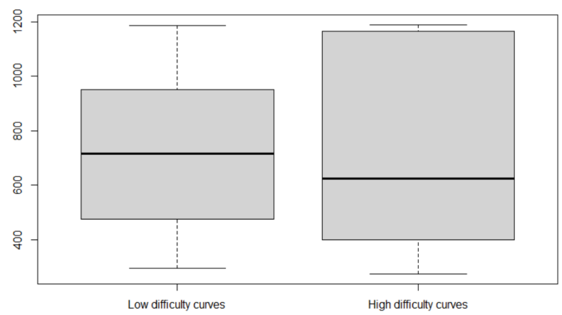


Fig. 4. Playtime of the participants, High difficulty vs Low difficulty
Results are not significant with a p-value of the Wilcoxon test ≈ 0.16. This means that overall difficulty did not contribute to the players' motivation in our experiment.

We decided to check the data from the GEQ in order to see if the player's experiences matches our results. The GEQ is composed of 7 components that we can class in two categories:

1. Positive components: Competence, Sensory and Imaginative Immersion, Flow, Challenge, Positive affect
2. Negative components: Tension/Annoyance, Negative Affect

Regarding our hypotheses, we are expecting that players who had a curve with peaks have higher positive score than the players who had flat curve, as well as lower negative score.

Using the data from the GEQ, we check the score of each component for each participant. We compare each curve with the three others for each component. We have significant results on the Competence and the Positive components for the Flow versus the Flow Peaks. The participants playing on the flow curve felt less positive emotion with a p-value ≈ 0.03 at the Wilcoxon Rank Sum test and less competence with a p-value ≈ 0.05 than the participants playing on the flow peaks curve. The other significant results are on the Positive and Competence components for the Flow versus Low Peaks. Again the participants felt less competence on the flow curve, with a p-value ≈ 0.03 and less positive emotion with a p-value ≈ 0.007. The Table 2 regroup the Location Shift for each significant results. It supports the results on the playtime and the hypothesis that people prefer difficulty curves with peaks.

6 Discussion

Our results confirmed that our participants preferred difficulty curves with peaks of difficulty. However, our participants are mainly gamers and they are all students. We decided to pass the experiment in a game development school to get

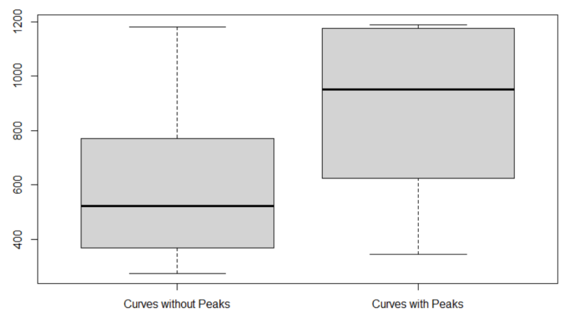


Fig. 5. Playtime of the participants, Peaks vs no Peaks. Wilcoxon Rank Sum test p $\approx$ 0.003 : difficulty peaks did contribute to the players' motivation in our experiment.

Competence	Flow	Positive	Flow
Low Peaks	-5*	Low Peaks	-5**
Flow Peaks	-3*	Flow Peaks	-3*

Table 2. Significant Location Shift of the Wilcoxon Rank Sum test comparing the results from the GEQ for each couples of curves.The Flow Curve is significantly lower than the two curves with peaks for the Competence and the Positive components.

rid of some bias like the learning of using a keyboard and mouse to play a game and the learning of basic FPS mechanics. This population is also close to the target population of FPS games. But our results are only valid for this game and this population, and we would like to replicate this experiment on a different public. The target public could be casual gamers for instance, maybe with different results.

As we said, we used a FPS game, mainly because it is a type of game based on motor skills, with a short period of learning, as the participants could learn the few mechanics of the game, the player's mobility, the gravity, the shooting rate, the reloading time, and the game's map in a couple of minutes, which let them play at their best potential afterward. FPS game are very often competitive. Our result might come from the fact that some of our participants are regular FPS players, and they may have taken the experiment as a competition. We cannot affirm that the same population of players will react the same on an adventure game like Zelda, and testing the same population on this type of game, would be very interesting. There exist different form of difficulty, and it would be very interesting to test the impact of difficulty curves on logical difficulty, for instance [8, 21, 4].

The FPS game we used is a one versus one battle arena game, which is a subcategory for FPS games. The players spawn in a small arena with a unique enemy. When the player fails, they simply respawn, and the game continues, thus failure is not punitive, but merely a quick negative feedback of the players failure to overcome the challenge. As Allart discussed, the punitive aspect of failure might influence the impact of difficulty on motivation. When a game proposes a difficult challenge that takes a long time to beat and must be restarted on failure, it creates tension, but failure can be much more frustrating, changing the impact of difficulty on motivation.

7 Conclusion

In this paper, we propose an experiment on difficulty curves. Many authors use difficulty curves in order to enhance the players' motivation, but few studies the impact of difficulty curves on the players.

For our experiment, we test a population of students as they played a simple battle arena FPS. This game is using a DDA model in order to adapt the difficulty to the players abilities, following a specific difficulty curve. Each participant played with one of four difficulty curves that we designed, to test the impact of base level and presence of difficulty peaks.

Results show the that players might prefer difficulty curves with peaks over flat ones. It is to note that we thought that the Flow curve would be the most enjoyed, but it seems to be the least preferred curve of all four. Thus, using a DDA model that is able to perfectly balance difficulty with player level, and thus simply aim for, a flat 50% chances of losing might not be the best idea for a FPS game.

8 Acknowledgement

This research is part of the *Programme d'investissement d'avenir E-FRAN* project *DysApp*, conducted with *Caisse des Dépôts* and supported by the French Government.

References

1. Allart, T., Levieux, G., Pierfitte, M., Guilloux, A., Natkin, S.: Difficulty influence on motivation over time in video games using survival analysis. In: Proceedings of the 12th International Conference on the Foundations of Digital Games. p. 2. ACM (2017)
2. Andrade, G., Ramalho, G., Santana, H., Corruble, V.: Extending reinforcement learning to provide dynamic game balancing. In: Proceedings of the Workshop on Reasoning, Representation, and Learning in Computer Games, 19th International Joint Conference on Artificial Intelligence (IJCAI). pp. 7–12 (2005)
3. Ang, D., Mitchell, A.: Comparing effects of dynamic difficulty adjustment systems on video game experience. In: Proceedings of the Annual Symposium on Computer-Human Interaction in Play. pp. 317–327. ACM (2017)

4. Aponte, M.V., Levieux, G., Natkin, S.: Measuring the level of difficulty in single player video games. Entertainment Computing **2**(4), 205–213 (2011)
5. Bandura, A.: Self-efficacy: toward a unifying theory of behavioral change. Psychological review **84**(2), 191 (1977)
6. Byrne, E.: Game level design, vol. 6. Charles River Media Boston (2005)
7. Constant, T., Levieux, G.: Dynamic difficulty adjustment impact on players' confidence. In: Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. pp. 463:1–463:12. CHI '19 (2019)
8. Constant, T., Levieux, G., Buendia, A., Natkin, S.: From objective to subjective difficulty evaluation in video games. In: IFIP Conference on Human-Computer Interaction. pp. 107–127. Springer (2017)
9. Demediuk, S., Tamassia, M., Raffe, W.L., Zambetta, F., Li, X., Mueller, F.: Monte carlo tree search based algorithms for dynamic difficulty adjustment. In: 2017 IEEE Conference on Computational Intelligence and Games (CIG). pp. 53–59 (Aug 2017). https://doi.org/10.1109/CIG.2017.8080415
10. ENJMIN: École nationale du jeu et des médias interactifs numériques, https://enjmin-en.cnam.fr/, accessed: 2022-07-11
11. Frazer: Level design and difficulty curves (2017), http://www.teaboygames.com/2017/06/14/level-design-and-difficulty-curves/, accessed: 2020-09-16
12. Gavin, A.: Making crash bandicoot part 6 (2011), https://all-things-andy-gavin.com/2011/02/07/making-crash-bandicoot-part-6, accessed: 2018-09-06
13. Gilovich, T., Medvec, V.H.: The experience of regret: what, when, and why. Psychological review **102**(2), 379 (1995)
14. Hao, Y., He, S., Wang, J., Liu, X., Huang, W., et al.: Dynamic difficulty adjustment of game ai by mcts for the game pac-man. In: Natural Computation (ICNC), 2010 Sixth International Conference on. vol. 8, pp. 3918–3922. IEEE (2010)
15. IJsselsteijn, W., De Kort, Y., Poels, K.: The game experience questionnaire. Eindhoven: Technische Universiteit Eindhoven pp. 3–9 (2013)
16. Ishihara, M., Ito, S., Ishii, R., Harada, T., Thawonmas, R.: Monte-carlo tree search for implementation of dynamic difficulty adjustment fighting game ais having believable behaviors. In: 2018 IEEE Conference on Computational Intelligence and Games (CIG). pp. 1–8. IEEE (2018)
17. Juul, J.: Fear of failing? the many meanings of difficulty in video games. The video game theory reader **2**(237-252) (2009)
18. Juul, J.: The art of failure: An essay on the pain of playing video games. Mit Press (2013)
19. Klimmt, C., Blake, C., Hefner, D., Vorderer, P., Roth, C.: Player performance, satisfaction, and video game enjoyment. In: ICEC. pp. 1–12 (2009)
20. Lazzaro, N.: Why we play games: Four keys to more emotion without story (2004)
21. Levieux, G.: Mesure de la difficulte des jeux video. Ph.D. thesis, Paris, CNAM (2011)
22. Linehan, C., Bellord, G., Kirman, B., Morford, Z.H., Roche, B.: Learning curves: analysing pace and challenge in four successful puzzle games. In: Proceedings of the first ACM SIGCHI annual symposium on Computer-human interaction in play. pp. 181–190 (2014)
23. Loftus, G.R., Loftus, E.F.: Mind at play; The psychology of video games. Basic Books, Inc. (1983)
24. Lomas, J.D., Koedinger, K., Patel, N., Shodhan, S., Poonwala, N., Forlizzi, J.L.: Is difficulty overrated? the effects of choice, novelty and suspense on intrinsic motiva-

tion in educational games. In: Proceedings of the 2017 CHI conference on human factors in computing systems. pp. 1028–1039 (2017)
25. Malone, T.W.: Heuristics for designing enjoyable user interfaces: Lessons from computer games. In: Proceedings of the 1982 conference on Human factors in computing systems. pp. 63–68. ACM (1982)
26. Miyamoto, S., Nakago, T., Tezuka, T.: The legend of zelda. Nintendo: Kyoto, Japan (1986)
27. Nakamura, J., Csikszentmihalyi, M.: The concept of flow. In: Flow and the foundations of positive psychology, pp. 239–263. Springer (2014)
28. Rao Fernandes, W., Levieux, G.: δ-logit: Dynamic difficulty adjustment using few data points. In: Joint International Conference on Entertainment Computing and Serious Games. pp. 158–171. Springer (2019)
29. Ryan, R.M., Rigby, C.S., Przybylski, A.: The motivational pull of video games: A self-determination theory approach. Motivation and emotion **30**(4), 344–360 (2006)
30. Spronck, P., Sprinkhuizen-Kuyper, I., Postma, E.: Difficulty scaling of game ai. In: Proceedings of the 5th International Conference on Intelligent Games and Simulation (GAME-ON 2004). pp. 33–37 (2004)
31. Strachan, D.: Making difficulty curves in games (2018), http://www.davetech.co.uk/difficultycurves, accessed: 2020-09-16
32. Sweetser, P., Wyeth, P.: Gameflow: a model for evaluating player enjoyment in games. Computers in Entertainment (CIE) **3**(3), 3–3 (2005)
33. Unity: Fps microgame, https://learn.unity.com/project/fps-template, accessed: 2020-09-15
34. Vazquez, R.: How tough is your game? creating difficulty graphs (2011), https://www.gamasutra.com/view/feature/134917/how_tough_is_your_game_creating_.php, accessed: 2020-05-05
35. Weiner, B., Heckhausen, H., Meyer, W.U.: Causal ascriptions and achievement behavior: A conceptual analysis of effort and reanalysis of locus of control. Journal of personality and social psychology **21**(2), 239 (1972)
36. Wilcoxon, F.: Individual comparisons by ranking methods. In: Breakthroughs in statistics, pp. 196–202. Springer (1992)
37. Yasuyuki, O., Katsuhisa, S.: Racing game program and video game device (2003), https://patents.google.com/patent/US7278913, accessed: 2018-09-18