Player-Centred Game Design: Player Modelling and Adaptive Digital Games

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ABSTRACT

We describe an approach to player-centred game design through adaptive game technologies [9]. The work presented is the result of on-going collaborative research between Media and Computing groups at the University of Ulster, and so we begin with a review of related literature from both areas before presenting our new ideas. In particular we focus on three areas of related research: understanding players, modelling players, and adaptive game technology. We argue that player modelling and adaptive technologies may be used alongside existing approaches to facilitate improved player-centred game design in order to provide a more appropriate level of challenge, smooth the learning curve, and enhance the gameplay experience for individual players regardless of gender, age and experience. However, adaptive game behaviour is a controversial topic within game research and development and so while we outline the potential of such technologies, we also address the most significant concerns.

Keywords:
Adaptive Games, Player Modelling, Artificial Intelligence

INTRODUCTION

It may be argued that much commercial game design is already player-centred because publishers and developers invest considerable time and money in market research and game testing. However, most current approaches focus on finding out what the player wants from the product before or while it is being made – primarily the developer's task – or by working out what will sell the game most effectively – often the publisher's task. Current developer player-centred approaches typically comprise practices ranging from the involvement of players in the

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development process by alpha/beta testing and play testing through to game patching after a game's release and making software development kits (SDKs) available for player game modifications (mods). In this way the developer is often concerned with tailoring the design of a game according to the requirements of a limited group of potential players. Publishers, on the other hand, are often more focused on reaching a wider group of consumers and so may encourage the developer to gear the game not only to their usual demographic but also to try and reach out to new players.

However, as Kline et al. [37] and Kerr [36] point out, publishers may not have as strong an interest in widening the appeal of games as they claim. They highlight the fact that software development is a risky business. Most products fail. This creates a powerful incentive to stick with the tried and trusted approaches and ride on the coat tails of proven success. Such reproduction gives game culture a strong tendency to simple self-replication, so that shooting, combat, and fighting games, once established, proliferate.

The approaches that we propose in this paper demonstrate that the accessibility of games may be enhanced while still satisfying the experienced gamer. It is possible to dynamically tailor a game to individual players (in-game) by using player modelling techniques [27] and adaptive game technologies [9]. These dynamic approaches reduce the dependency on collecting data about player requirements and the player demographic. By focusing on variations in learning and playing styles and correlating these with personality profiles (for example) we may avoid the problems created by stereotyping players on the basis of age or sex [34]. Some research indicates that females purchase games less often [46] than their male counterparts and while this is not a straightforward issue, adaptive game design may offer a partial solution to the gendered nature of digital games as a cultural activity.

Every player is different; each has a different preference for the pace and style of gameplay within a game, and the range of game playing capabilities between players can vary widely. Even players with a similar level of game playing ability will often find separate aspects of a game to be more difficult to them individually, and the techniques that each player focuses on to complete the various challenges a game offers can also be very different. This is at the core of our reasoning that adaptive game technology can have an important role to play in next-generation games. It can be used to moderate the challenge levels for a player, help players avoid getting stuck, adapt gameplay more to a player's preference/taste, or perhaps even detect players using or abusing an oversight in the game design to their advantage ('exploits'). Players often use 'exploits' in order to make it easier for them to succeed in the game even if their enjoyment of the game may be lessened because of the reduced challenge. That is, players will often repeat a successful strategy over and over again because it leads to a predictable win, even if it ruins the game to a certain extent.

Important issues such as the deficiency of game completions by players, teaching players effectively, the problem of "beginnings" [51], as well as the niche quality of current games and their lack of accessibility to a wider market [54] are relatively well known both within the games industry and the games research community. However, these are only beginning to be addressed properly. Much current player-centric game design uses straightforward approaches such as empowering players to control the quality of their own gameplay experience by providing enough flexibility and variety in gameplay choices. Some games incorporate in-game player support systems, such as hints in the form of visual clues in the landscape, NPC guidance, or maps suggesting a way forward. Other games are more responsive to an individual player, for example, in “Crash Bandicoot 3: Warped” (SCEA, 1998) if a player repeatedly fails at the same point in the game then a mask is provided to the player character which acts as a shield, and in “Mario Kart 64” (Nintendo, 1996) where “rubber banding” is used to help weaker players.

It is especially rare to see the use of dynamic technology within games that is responsive to individual players. One quite well-known attempt at this type of technology is the “auto-dynamic difficulty” approach in “Max Payne” (Take 2 Interactive, 2001) [47]. In this game the difficulty level is altered by increasing the numbers of enemies in a room (or the difficulty of killing them) by observing features of the player’s game playing. Statistics on a player’s average health, shot accuracy, number of times shot, numbers of times killed, etc. may be recorded to help make a decision in-game as to how difficult the game should be for the player. The approach that we propose resembles “auto-dynamic difficulty” in the dynamic response to a player in-game. We believe that dynamic modelling techniques along with adaptive mechanisms that alter the game according to the needs of an individual player can provide the game designer with an effective alternative approach to game design, and we will discuss our reasons for this throughout the rest of the paper.

CURRENT APPROACHES TO PLAYER-CENTRED GAME DESIGN

Many current structured approaches for player centred game design are rooted in research into human factors from the mainstream computing realm and for many years this type of research has argued for about the importance of a user-centred approach when designing software. Considerable research has been performed on user-centred design for productivity software within the general computing domain, e.g. office applications, but ideas and theories that specifically address user-centred game design are only beginning to be constructed. It is important to keep in mind, however, that there is an important difference between usability and playability. As Kücklich [38] points out: "While increasing the usability of a media technology usually means making its functionality as accessible as possible to the user, playability often depends on withholding certain options from the player. It is quite crucial in many games that the player does not have access to the full range of options the game offers initially, but only after the player has invested some time in the game. The playability of a game is actually increased by this strategy of deferral, because it challenges the player to spend an increased amount of time playing the game."

Nevertheless, it has been shown that software usability methods can be applied to digital games in order to improve user satisfaction and decrease task-based failure and error rates among users. Research methodologies frequently used in computer systems design – especially in user interface design and experimental psychology – have also been applied to the evaluation of games: user studies [13] and heuristic testing [17, 19, 43] are two such approaches. Much of the evaluative studies performed with gamers concentrate on evaluating a game by observing players and/or by asking players a series of questions designed to find out the subject’s opinions on a range of issues such as gameplay, game story, mechanics and usability [14]. Additionally, it is widely accepted that there will be many groups of people involved in user-testing: developers, publishers, programmers, artists, marketing personnel and even licence-holders – not forgetting gamers themselves - hardcore gamers, first-timers and social gamers.

Microsoft’s user-testing group [21] suggests that evaluation of games can take a number of guises, including observing individuals and groups in a variety of settings (out-of-game and in-game) and performing usability tests or surveys. Gamboa et al [23] suggest that there are several advantages to questionnaires: they can get unbiased individual responses, provide hard numbers, collect subjective data, be used for evaluations, be generalised to a population and provide for subgroup analysis. Noted weaknesses of questionnaires are that the answers you get relate to the questions you ask (are you asking the right questions?), collecting behavioural data is not easy, questionnaires can be time-consuming and costly and they can suffer from sampling problems. Focus groups, another popular technique, also suffer from particular strengths and weaknesses.

All of the above activities, if carefully orchestrated, can lead to a better understanding (for designers of games) of how players can get more fulfilment from a game, but there are significant challenges in designing the evaluation procedures. Involvement of real gamers is important, but representative samples of intended target groups must be engaged; subjective observations need to be recorded and interpreted correctly and tests or surveys must be constructed using meaningful and valid heuristics. Fulton [20] reports on the challenges of getting good feedback and the difficulties of ensuring it can be delivered to the development team in a timely and meaningful way. If performed early in the development lifecycle such techniques can lead to a better game – indeed Pagulayan reports that the impact can be significant [49], although the costs can be high and there is never a guarantee of success [22]. It is clear, though, that most of the current effort in this area is in terms of user-testing the game before it is released, and not, as we propose, to develop a better understanding of players in order to adapt the game dynamically, after release.

Pagulayan et al [48] highlight some of the crucial aspects of effective user-centred game design and many of these relate to our reasons for investigating adaptive game technologies. For example, they point out the importance of getting the levels of challenge right for players and dealing with the different skill levels of players. They state that a choice of easy-normal-hard levels at the beginning of a game is not normally an effective mechanism for differentiating between different player abilities – an argument also made by game designer Scott Millar [47] in advocating the auto-dynamic difficulty technology of “Max Payne”. Players rarely choose anything other than a normal difficulty mode and Millar argues that with the rate of technology improvements in other areas of game development it is a shame that many games still deal with the difference in player ability in such a simplistic manner. The issue is to “maintain the challenge, reward and progress for the unskilled player without severely hampering the skilled player” [48]. Pagulayan et al [48] also point to the value of intrinsic over extrinsic reward in that players are more likely to continue to play if they feel powerful and clever [44]. Rather than reward players only with new weapons, power-ups and content we need to provide opportunities for a player to succeed in a game by overcoming challenges (at or just above their skill level for their gameplay preference).

The importance of maintaining the right level of challenge is underlined by the research conducted by Csikszentmihalyi and Csikszentmihalyi [12] on flow: "The universal precondition for flow is that a person should perceive that there is something for him or her to do, and that he or she is capable of doing it …. Optimal experience requires a balance between the challenges perceived in a given situation and the skills a person brings to it". In other words: flow is the experience of hitting the 'sweet spot' between the annoyance of a task that is perceived as trivial and the frustration of a task that is perceived as too difficult. This is also described as a balance between challenge and competence, or between complexity and boredom. Therefore, one of the goals of adaptive game design should be to keep the player in a state of flow by increasing the difficulty when the game appears too easy for the player, and decreasing it when it appears to hard.

Hopson [26] investigates contingencies in game design (contingencies are rules which govern when a reward is provided), suggesting that variable ratio contingencies and variable interval contingencies may lead to more activity, challenge, and, by implication, more enjoyment. Here we see a questioning of the 'one colour suits all' premise which to date has been pervasive in games and this question re-appears in Cornett's work [11]. Cornett's research indicates that for certain game genres – especially MMORPGs – new players inexperienced with the genre may require specific support to get them to engage with the game. One approach suggested by Bateman [3] is that there may be value in user profiling for game design: specifically in applying the Myers-Briggs typology to gamers. This may lead to better understanding of the types of people most likely to play games of a particular genre. Questions arising from this include whether or not particular game genres can be opened up to new (different) types without 'losing' established player types. Understanding, categorising and modelling players as we will see in the next section is not a trivial task. However, the effective modelling of players is an important aspect of adaptive technologies and a new form of game: one which reveals itself in different ways depending on the player type and according to particular play styles.

UNDERSTANDING AND MODELLING PLAYERS AND NON-PLAYERS

An essential aspect of effective adaptive game design is in understanding game players in order to model them accurately. By understanding players, we do not only mean working with existing game players through play or usability testing – we also mean conducting empirical research in public and private game spaces into the culture and experiences of digital game and non-game players. Unfortunately much of this work is highly localised and small scale – yet it does throw up some interesting issues.

A survey (see Table 1) conducted by the Computer Entertainment Software Association (CESA) in Japan in 2001 found that the numbers of people who 'still play' games has decreased to 27.8 percent while the numbers that had stopped playing had increased between 2000 and 2001 [7]. CESA categorised their total population into four consumer categories: active, dormant, prospective and disinterested. Disinterested customers were those who had never played and did not want to, or had played and had no intention of playing again. These constituted the largest proportion of those surveyed at 35.8 percent. Dormant customers were players who were waiting for games to be made which would make them want to play again. These constituted 28.1

percent. Only 27.8 percent were described as active players, down from almost 40 percent in 1999.

Table 1 Categorisation of Gaming Customers in Japan, 2001 and 1999[1].

		2001 General Public	1999 General Public
Active Game Players		27.8 %	39.3%
Dormant	'I used to play but now stop playing. I want to try again only if any software interests me'	28.1 %	24.3%
Prospective	'I have never tried but I want to try if any software interests me'	8.3 %	12.2%
Disinterested	'I have never tried and I won't' and 'I used to play but I won't anymore'	35.8 %	24.2%

Source: CESA, 2002:58-62

While dormant customers were divided almost evenly between males and females, females constituted a larger proportion of the prospective and disinterested groups. In addition, while the average age of active game players was 23.4, the average age of dormant customers was 31.6 years. Prospective and disinterested players were aged 33.4 and 37.2 years respectively. Clearly the industry has a large potential market of females and people aged above 25 years, which it is not as yet satisfying, at least in Japan. People in the non-active groups responded that they were too busy with work to play games, games were too complicated or games were not fun.

Industry surveys like this one both challenge and reinforce certain stereotypes. While more females and people over 30 years of age are playing digital games than in previous decades, the most frequent game players are males, by a factor of two, and the highest proportion are aged between seven and twelve years. The Japanese survey also points to the perceived limitations of current game software and the need for a greater range of software if dormant and prospective consumers are to be reached. More radical tactics may be needed to reach disinterested consumers. Surveys like these point to a large potential market which remains unsatisfied or unmoved by current games.

When we start to review current studies of game players the picture is arguably even more complex. While survey after survey points to increasing rates of 'access' to digital game playing platforms [15, 16] most large surveys tend to hide a range of barriers which more ethnographic and interview based research starts to uncover [42, 37, 33, 36, 59, 60]. Thus we find that content is only one of the factors which influence who plays, how often and how. We also find that player preferences and pleasures cannot be easily mapped on to content types or genres – hence the problems faced by existing user centred design and usability testing of specific titles [53, 35].

[1] Percentages for total population based on generalisations made from original samples of 1,013 in 2001 and 1,111 in 1999.

As Richard Bartle [1] points out ‘400,000 people play EverQuest, but 600,000 other people who bought the boxed set don't play it.’

Research that tries to differentiate between different player types often tends towards overly simplistic categorizations – such as the binary opposition between casual and hardcore players – or, conversely, towards highly specific typologies such as Bartle's [2] observations of different behavioural traits in online games. A player typology for adaptive game design thus faces a twofold challenge: it must be specific enough to allow for widely different play-styles as well as general enough to be applied across different genres, platforms and cultures.

This dilemma points at a potential contradiction between adaptive game design and emergent gameplay. If adaptive game design is to be understood as a top-down-approach that attempts to create a 'prescriptive' player typology which can then be used to make the gameplay more enjoyable for players, this requires gathering a large amount of gameplay data in order to be able to anticipate all the possible ways a game could be played. If, on the other hand, adaptive game design is to be understood as a bottom-up-approach that aims at achieving adaptivity by emergence, this requires an absence of pre-conceived ideas about which forms play in a specific situation might take.

From a cultural point of view, it seems obvious that the top-down approach must necessarily simplify the complexity of gameplay behaviour in order to succeed. A player typology that attempts to anticipate different styles of play simply cannot take into account all the factors that might potentially influence the gameplay experience. Conversely, from a technical point of view, it seems obvious that a level of emergence that would be able to adapt to every possible play-style is impossible to implement within the limits of current technology.

For the time being, we must keep in mind that our aim is not to create a perfect adaptive system, but to propose ways of achieving more adaptivity within existing game architectures. At present, all we can do is point out ways of using the potential of current computing technology to enhance the enjoyment of people who already play games. Dynamic player modelling seems especially promising in this respect as it allows for a form of game design that creates a heuristic player typology 'on the fly'. However, we would like to stress the fact that a higher level of adaptivity, which might also attract new types of players, requires a fundamental change in the way games are designed. Truly adaptive gameplay can only be the result of a design strategy that embraces emergence and yields a high level of control to the player.

ADAPTIVE GAME DESIGN

Adaptation may be defined “as ability to make appropriate responses to changed or changing circumstances” [30] and as biological creatures use this form of problem solving regularly it is not surprising that many of the techniques used in computing to build adaptive system are actually based on nature [61], e.g. artificial neural networks, case base reasoning systems, artificial immune systems, or evolutionary algorithms. Adaptation as such is strongly connected to learning and we may use it to learn about a player in order to respond to the way they are playing, for example by adjusting a computer opponent’s strategy [28] so as to present a more appropriate challenge level. Learning and adaptation are viewed by some as a having a crucial part to play in next-generation games. For example, Manslow [45] states that:

> "The widespread adoption of learning in games will be one of the most important advances ever to be made in game AI. Genuinely adaptive AIs will change the way in which games are played by forcing each player to continually search for new strategies to defeat the AI, rather than perfecting a single technique."

A game may be adapted through changes to:

1. A player's character
2. Non-player characters in the game
3. The game environment or game state

The first of these is perhaps the most interesting because an alteration of the player character in this way can lead to a greater sense of embodiment. Although it doesn't quite relate to adaptation, Poole provides an example from "Metal Gear Solid 3: Snake Eater" (KCEJ, 2004) [52] to illustrate how a player's actions can alter the state of their player character and so how they play. If their character gets hurt there is a consequence to the player character's wellbeing and the gameplay – if the character has been injured then progress is hindered until the injury is treated. This feedback loop of action-consequence-action can instil a great sense of embodiment that increases immersion in the game. The use of player modelling and adaptation may lead to the same sort of sense of embodiment if the adaptation directly affects the player character for appropriately designed games.

The most obvious way to adapt a game is to change the difficulty level of non-player character opponents or modifying the behaviour of friendly non-player characters – depending on the type of game. Non-player characters can be used to provide clues or support to a player according to their needs and playing preferences. In fact there are a host of imaginative ways in which a variety of non-player characters can be used to affect the choices open to the player and even altering the game narrative.

The game environment can also be modified in response to the player – this can be anything from increasing the number of items that can be picked up, e.g. heath, bullets etc. through to the actual landscape and topography of the world changing. The designers of the RPG "Fable" (Microsoft, 2004) set out to create a game world where the game landscape would change in response to a player's evolving character and the actions that they performed – if they were evil then the world would become corrupted before their eyes and the opposite being the case if they were good. In the end most of the more ambitious aspects of this technology were not realised in "Fable" but this game still demonstrates the possibilities of the technology. A player may enjoy a heightened sense of immersion and enjoyment in playing a game if they feel that the game is responsive to them as an individual.

Though there are only a few practical examples of the use of adaptive technologies in current commercial games and game research [25, 57], successful research in related areas demonstrates the potential of this technology – particularly research on Intelligent Interfaces [41] and Intelligent Tutoring Systems which is very focused on user modelling and adaptation [4, 6]. Our approach has some similarities to recommender systems for online e-commerce stores – for example the CEO of Amazon, Jeff Bezos, has been quoted as saying “If I have 2 million customers on the Web, I should have 2 million stores on the Web” [56]. In the same way we wish to design game systems that provide each player with a separate experience.

We suggest a framework for adaptive games based around the system illustrated in Figure 1. The modelling of players is a crucial aspect of this approach because if our models are inaccurate or inappropriate then the whole system falls down. In addition, as explained previously, how we choose to differentiate between players is not normally a straightforward issue, and in fact this process will vary between game genres. We believe that we should not assume that our modelling is always flawless and we should not only take care about selecting the variables that define player characteristics, but for many games it would be useful to provide player preferences to the system to form part of the player model. As Manslow points out it is wise to use as much useful prior knowledge in the model as possible [45].

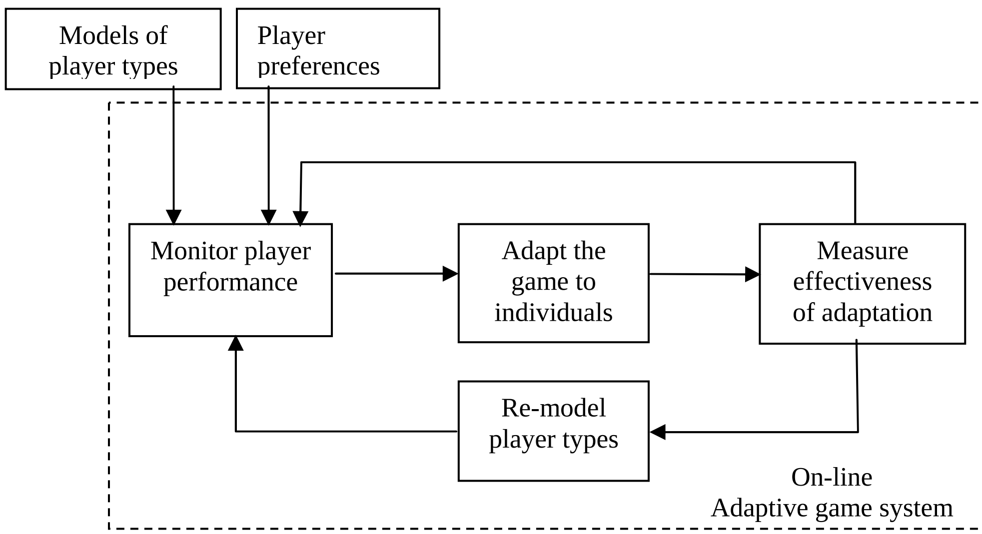

Fig. 1: A potential framework for an adaptive game system.

The feedback loop in this system provides an element of control in the system so that if a model no longer fits as a player learns to play the game, then the player may be shifted to an another existing population profile i.e. using population shift ideas [31], or if none exists, a new profile can be created. Another affect may be more drastic, where the rules that depict a model no longer represent the players efficiently and so re-modelling is required because of concept drift [5, 62]. Naturally, players will learn and adapt to the game as they play. Some players will learn faster than others and additionally, various players tend to excel in different aspects of the game – each player plays and progresses in their own unique way. Therefore, the models that we use at the beginning of the game may no longer be entirely appropriate as the game develops. Perhaps the reclassification of a player (due to population shift) will suffice in some cases; however it may be better to account for a concept drift in our original classification by updating our models on the basis of new data. In many cases the drift may be slight but this can still have a significant impact on the response of the game to the player, especially if the drift continues over a long period of time.

Adaptation algorithms may or may not incorporate machine-learning but the system adopted must potentially be able to operate within the gameplay session[2] in real time. The effects of adaptation on the player can be monitored quite easily by observing game data, checking how quickly a player is progressing, monitoring the length of gameplay sessions and other similar in-game data. However, this type of data may not be satisfactory by itself and it may also be useful to monitor player emotions [58] such as frustration levels [24] by taking measurements from game control pads [58] or more advanced sensors.

Most existing approaches to player modelling are based on working out how the player should be modelled using in-game variables and then developing a player model by observing and recording data from these variables for each player. More complex player information is much harder to model as we require a better understanding of player behaviour and more care needs to be taken in pre-constructing the framework for the model – we may not be able to construct a model by observing simple statistics in the data. However, models with this sort of higher order player profiling may be more useful for ensuring a more appropriate adaptation to individuals, as research has demonstrated in other fields, such as fraud detection [18]. One possible approach for forming a more complex or higher order profile of a player is to use a factorial model like the one shown in Figure 2.

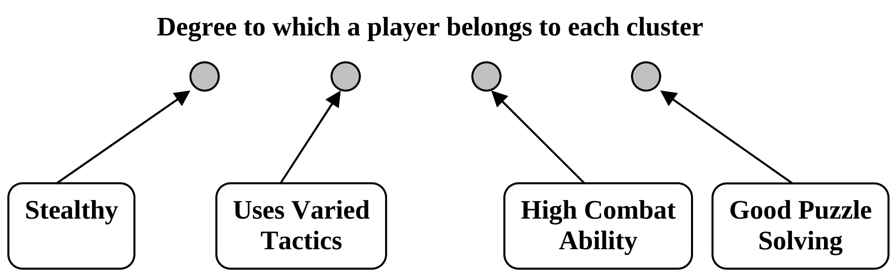

Fig. 2: A factorial approach to player modelling

This example could be used for an adaptation mechanism in action-adventure games – other types of games would require a different set of factors. Using this approach we may manually partition data space to attach different meanings to various aspects of the data, i.e. the stealthy factor would be informed by a number of independent game variables that can tell us about a player's stealth level in a game. In the example above, each player would have a four factor profile with four real numbers in the range of 0 to 1 that uniquely identify each player's playing characteristics. For example, a player with a numerical profile of (0.8, 0.2, 0.2, 0.5) may tend to prefer to play a game by avoiding direct, close-up conflict. Of course, there are some difficulties with setting up this sort of model and working out which game variables to use and how to partition them so as to be useful in identifying independent traits of player behaviour. An experienced game designer may be able to work this out manually by trial and error. However, it is also possible to use data mining tools [32, 50] or unsupervised statistical techniques such as factor analysis [63] to identify correlations between the variables and then we can attach a meaning to them. We must also put an interpretation on the combinatorial patterns of the game

[2] This may not need to be the case if some of the "number crunching" is performed between levels or at other processor friendly times.

playing factors for each player. There are many methods from the realm of AI that can be used to implement this technology.

Several issues need to be addressed about adaptive game technology. One concern is that players may disapprove of the technology because it may result in a game experience that differs for each player and therefore players can't easily compare experiences and/or brag about their successes. However, it must be noted that there are two opposing player desires to take into account:

1. The desire of a player to learn the rules so as to master the game.
2. The avoidances of "sameness" or lack of variety of gameplay.

We believe that the benefits of adaptive games to the majority of players (particularly beginners) in terms of tailoring an appropriate level of challenge and gameplay style for a player – not to mention replay value – outweigh the drawbacks. Players already modify their own gameplay through cheats, guides, walkthroughs, and modifying games [39] to enhance the game experience, and so there is a precedent for the use of adaptive technology for a similar purpose.

A second concern relates more to the profiling and modelling aspects of the technology, which assumes that a particular game save will always be used by a single person. While this generally is the case with PC games it is often not the case with console games because the playing of a game (on a particular game save) may be shared by several friends or family. This is a significant issue currently but as next generation consoles begin to appear, online play and thus logon from a console will become more prominent – and perhaps user switching as used on PC operating systems may come into use. As gamers become more connected in the next generations of gaming hardware then the potential for online profiling will increase rapidly. One can imagine a player storing a game profile on a remote server for use in online games but also having the choice to logon to this profile for single player (non-networked) games so that the gameplay may be adapted to their particular profile. Microsoft already use a limited form of player profiling on their Xbox Live network for "player-matching", however, there is much more scope in this technology for accurately tailoring the gameplay experience to the player and finding appropriate players to play with or against through more advanced player models and profiles.

Another concern often raised relates to the difficulty of testing adaptive products and the extra time that is required in development. Using adaptive technology in-game, particularly with machine learning, inevitably means that the game often cannot be fully tested. Many game publishers require a guarantee that a game has a very low percentage of game bugs and that they do not significantly impact the key aspects of the gameplay. If adaptive technology is responsible for introducing an unforeseen but significant game bug, then players could be entitled to a refund which would be serious issue for both the publisher and the game developer. The emergent or unpredictable properties of adaptive technology make the design of a game more challenging but this should not prevent us from being adventurous because the rewards are potentially great. For example, if the adaptive technology is restricted by architectural design as it is for the learning of the creature in "Black and White" then problems can be constrained and controlled so that gameplay can only be altered in restricted ways and within pre-determined boundaries.

CONCLUSION

There are many approaches to player modelling, and in fact you could argue that digital games inherently have an in-built model of players because the designer has a specific type of gamer in mind when they design the game (even if they do this subconsciously). In this paper we have proposed an approach through which a game developer can make a more conscious effort to model players in a game's design and development. By adopting a framework similar to the one that we have suggested, a game may be designed to be more responsive to a wider range of players by incorporating dynamic models of different players into the game technology.

We believe that the potential benefits of adaptive technologies in games are clear, however, the effective incorporation of the technology into games is not without difficulty. For example, as discussed earlier, player preferences and pleasures cannot be easily mapped to content, gameplay, or genres – though this should be more easily handled by adaptation. Additionally, if we are to define a player typology for adaptive game design, it must be specific enough to allow for widely different play-styles but general enough to be applied across different genres, platforms and cultures. However, with the adaptive approach that we have discussed it is not necessary to categorize players rigidly a-priori but by designing flexibility into the adaptive technology, accurate models can be developed dynamically during the game. That is, the combination of relevant prior information on typical player typologies along with specific in-game data can be used to construct the most appropriate model for a player.

To progress our work in this area, future work will focus on developing our understanding of the differences in players in order to inform the design of player models and suitable associated adaptive technology. Using these models we will implement a variety of adaptive systems for games to test the effectiveness of the approach and in particular investigate approaches that dynamically re-model the player by identifying and distinguishing between population shift and concept drift. We plan to test the technology in a number of bespoke small scale games.

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