Baldwin, Alexander, Johnson, Daniel, & Wyeth, Peta
(2016)
Crowd-pleaser: Player perspectives of multiplayer dynamic difficulty adjustment in video games. In
CHI PLAY '16, 16-19 October 2016, Austin, Texas.

https://doi.org/10.1145/2967934.2968100

Crowd-Pleaser: Player Perspectives of Multiplayer Dynamic Difficulty Adjustment in Video Games

Alexander Baldwin
Queensland University of Technology
Brisbane, Australia
alexander.baldwin@qut.edu.au

Daniel Johnson
Queensland University of Technology
Brisbane, Australia
dm.johnson@qut.edu.au

Peta Wyeth
Queensland University of Technology
Brisbane, Australia
peta.wyeth@qut.edu.au

ABSTRACT

Multiplayer Dynamic Difficulty Adjustment (MDDA) features are becoming increasingly common in competitive multiplayer video games as a means to balance challenge between differently-skilled players. However, without a thorough understanding of how MDDA design is perceived by players, it is difficult to predict how players may feel about its use. A mixed-methods approach combining an online survey and interviews was conducted with multiplayer game players to investigate player expectations regarding the effect of different components and attributes from the MDDA Framework on the play experience. As well as highlighting similarities and conflicts between the perspectives of low and high-performing players, patterns emerged demonstrating that players value control, personal benefit and awareness of MDDA use. Along with additional design considerations suggested, this led to the refinement of the MDDA Framework through the introduction of an 'Awareness' component.

Author Keywords

Challenge, Balancing; Video Games; Design; Multiplayer Dynamic Difficulty Adjustment;

ACM Classification Keywords

K.8.0 [Personal Computing]: General - Games

INTRODUCTION

Optimal design of video games requires a thorough understanding of the player experience and variables that affect enjoyment [22]. This holds particularly true for multiplayer games and other 'games as a service', in which long-term player retention is required for growth and profitability [6]. In competitive games, the sense of competence is a driver of motivation to play and replay intention [17]. Theories of optimal player experience such as GameFlow [22] and Player Experience of Needs Satisfaction [20], as well as more general psychological theories such as Self-Determination Theory [9] and Flow [8], agree that the matching of player skill level to the challenge presented by the task are necessary for optimal intrinsic motivation and feelings of competence, satisfaction and engagement. Confirming this need, Clarke and Duimering [7] found that the most frequently mentioned negative aspect of play online multiplayer first-person shooter games was unmatched challenge or skill. Multiplayer 'matchmaking' systems such as TrueSkill [14] attempt to address this through matching players of similar skill together in a match. However, these systems are restricted to online play with large player populations and unable to react in real-time to differing player performance.

In single player games, reactive systems such as Dynamic Difficulty Adjustment (DDA) can dynamically balance challenge through the manipulation elements such as AI agent behaviour [1], timers [10] and the game environment [15] in real-time during play. As the game obstacles and possible variables have been planned and the bounds of their manipulation set by the designer, it is possible to predict player responses to these systems [24]. However, DDA techniques cannot be directly applied to multiplayer gameplay in which challenge is provided by competition between human players. This presents difficulties for multiplayer designers by restricting the factors available to manipulate in order to balance challenge. For a DDA system to be effective, it must be able to measure the level of difficulty the player faces at any given moment [1], a feat more easily achievable in single player games in which game-controlled obstacles are measured against player skill [18]. Multiplayer gameplay can confound this through the need to compare player skill against others. Consequently, the effect of any one change can affect the challenge and experience of other players present too.

While there is increasingly widespread usage of DDA-like features in multiplayer gameplay modes for commercial game releases, research has only recently begun to explore their use, associated impacts on the player experience and how players may perceive their inclusion. Baldwin and colleagues [3] refer to these multiplayer-specific systems as Multiplayer Dynamic Difficulty Adjustment (MDDA). An MDDA 'instance' is a gameplay feature in competitive multiplayer video games designed to reduce the difference in challenge experienced by all players through adjusting the potential performance of certain players [3]. An existing

CHI PLAY '16, October 16-19, 2016, Austin, TX, USA
© 2016 ACM. ISBN 978-1-4503-4456-2/16/10…$15.00
DOI: http://dx.doi.org/10.1145/2967934.2968100

example of MDDA in a commercial game is present in the combat racer *Mario Kart 7*. During a race, lower-ranked players have an increased chance of receiving more effective weapons from 'random' weapon pickup boxes. This allows lower-performing players an increased chance of improving their ranking against high-ranked players with less powerful weapons.

Research exploring the impact of MDDA techniques has confirmed the effectiveness of some techniques (in terms of allowing differently skilled players to compete with more balanced performance) as well as positive effects on enjoyment in a variety of contexts. These include manipulating steering, speed and acceleration in racing games [5] and input assistance in a first-person shooter [23]. Beyond balancing inherent skill, dynamic performance balancing has also been tested between players with and without mobility disabilities using physical inputs for a dance game. Gerling and colleagues' [13] found MDDA features to be an effective method of balancing between players with differing physical ability and means of control. However, they note the risk of over-balancing (normalising performance too much) as a large difference between expected performance and actual in-game performance may threaten self-esteem and wellbeing. Conversely, Vicencio-Moreira and colleagues' [23] testing of different strengths of balancing suggest stronger balancing (greater performance adjustment) may be most enjoyable, although also the most noticeable.

Bateman, Mandryk, Stach and Gutwin [4] investigated differing methods of control assistance in a target shooting game and found them to be an effective method of balancing performance between differently skilled players, with combinations of methods able to provide stronger balancing. However, they caution that participants were divided on the issue of MDDA awareness with no clear consensus on whether players should be informed of the use of performance adjustment [4]. This highlights player preferences as an area of MDDA research worthy of further attention, as much dynamic balancing research has focused on specific implementations without a broad perspective on player perception of MDDA types and use. How players perceive differing types of MDDA is of particular importance compared to single player DDA, as MDDA directly adjusts the performance of the players themselves rather than simply modifying the surrounding game elements.

In our previous published work, a framework of MDDA was created to allow for the classification of MDDA instances by breaking them down into their components and attributes [2]. In this paper we seek to provide insight into the effect of individual framework components on the player experience of both low and high-performing players. This is achieved through addressing three primary aims:

- Investigate player perceptions of MDDA component attributes using the MDDA Framework.
- Determine the similarities and differences of the likely impacts of MDDA on the player experience from the perspective of low and high-performing players.
- Use player preferences and feedback to identify necessary refinements to the MDDA framework.

This study forms part of a larger program of research, in which we aim to create a more thorough understanding of player preferences for differing types of MDDA. While future studies are planned to test the effects of MDDA during gameplay, the current study focuses on player expectations regarding the impact of MDDA on the player experience. We consider expectations to be of interest as a player's expectations will inform their decision to buy/play a game in the first instance (regardless of whether player expectations align with actual in-game player experience). The findings from our larger program of research are intended to help designers make more informed decisions regarding how to balance player performance in a way that minimises interference with other aspects of the player experience. In the current study our findings are limited to players' expectations regarding balancing techniques. Additionally, by exploring preferences from differing perspectives (i.e., when a relatively low performing player vs as a high performing player) we seek to identify the aspects in which players believe an improvement in experience for one group may come at the cost of the other.

MDDA FRAMEWORK OVERVIEW

The previously-created MDDA Framework [3] consists of seven components common to all MDDA instances, irrespective of genre or game (see Table 1). Each component has several possible attributes or states, of which any particular MDDA instance will utilise one or more for every component. This allows any MDDA instance to be described using the framework by specifying its component attributes. The seven components and associated attributes are listed and defined below.

Component	Attributes
Determination	• Pre-gameplay • Gameplay
Automation	• Applied by system (automated) • Applied by player(s) (manual)
Recipient	• Individual • Team
Skill Dependency	• Skill dependent • Skill independent
User Action	• Action required • Action not required
Duration	• Single-use • Multi-use • Time-based
Visibility	• Visible to recipient • Visible to non-recipients • Not visible

Table 1. MDDA Framework overview

Determination
The Determination component refers to the game state or time in which the decision to use the MDDA instance is made. The attributes of this component are:

Pre-gameplay: the decision to use the instance is made before the multiplayer game match commences, based on past performance.

During gameplay: the decision to use the instance is made in real-time during the multiplayer match based on current performance.

Automation
This component indicates whether the decision to use the MDDA instance is automated by the game system or chosen by the player(s) themselves. The attributes of this component are:

Applied by system (automated): the game system automatically determines the need for an MDDA instance and applies it. This relies on the game possessing a means of determining relative player performance, such as TrueSkill's player rankings [21].

Applied by player(s) (manual): players choose to use an MDDA instance based on their own judgment. This is currently widely applied in the fighting game genre, with players able to choose to distribute health handicaps before a match begins by providing increased player health for low-performing players.

Recipient
The recipient of an MDDA instance refers to the player(s) intended to be affected by the instance. The attributes of this component are:

Individual: the instance is intended to affect a single player.

Team: the instance is intended to affect a group of players (only possible in team-based gameplay modes).

Skill Dependency
This component indicates whether the low-performing players are required to act with some degree of skill in order to improve performance. The attributes of this component are:

Skill dependent: the player(s) must respond, react or make-use-of the effects of the MDDA instance with a degree of skill in order for it to impact their performance. This refers to the instance providing the *opportunity* for an improvement or reduction in performance; not a guarantee. For example, providing increased movement speed in a first-person shooter game does not guarantee a higher number of player 'kills' but may allow the player a better chance to do so if they act with skill.

Skill independent: the player(s) do not need to act with any degree of skill in order for their performance to be affected by the effects of the MDDA instance. In this case the effect applied is linked to the objective and winning conditions of the game by adjusting the player's performance irrespective of their behaviour. For example, reducing damage taken

User Action
This component dictates whether the intended recipient of the MDDA instance is required to interact with the interface in order to initiate the instance's effects. The attributes of this component are:

Action required: the recipient must interact with the interface in order for the effects of the instance to begin (e.g., pressing a button to activate the effects).

Action not required: the effects of the instance will commence without player interaction with the interface.

Duration
This component indicates the time-based property of the MDDA instance. The attributes of this component are:

Single-use: the effects of the instance occur at a single moment. For example, a single boost to the player's health.

Multi-use: the effects of the instance may occur multiple times. For example, the player is given three health boosts they may activate over the course of the match.

Time-based: the effects of the instance occur continuously over a certain timeframe. For example, the player's health may recharge gradually over 30 seconds of play.

Visibility
This refers to whether players of the game are provided with feedback regarding the presence of the MDDA instance. The attributes of this component are:

Visible to recipient: feedback is provided to the recipient of the instance, with the intention to inform him/her of the potential performance adjustments enacted by the instance. This may occur via visual, audio, or tactile means within the game such as a text notification in the game's Heads-Up Display (HUD).

Visible to non-recipients: feedback is provided to the non-recipients about the effects and/or recipient of the instance. This can occur through the same methods listed above, but can additionally include the identity of the recipient.

Not visible: no feedback is provided to any players in the match that the instance is in effect. While experienced players may deduce the presence of an MDDA instance through observed variations to the game rules, no explicit feedback is provided to any players.

METHOD
To investigate player perception of the influence of MDDA features on their player experience, an online survey was crafted to reach a broad range of participants across multiple game genres and formats. Additionally, supplemental interviews with players of multiplayer games were conducted to provide better interpretation of and insights into player preferences expressed in the survey. For both methods, participants (as players of multiplayer

games) were likely to have been exposed to balancing techniques in various games including examples discussed. However, no participants were familiar with the formalised MDDA Framework prior to this study.

Survey

Participants were required to be aged 17 or over with any level of multiplayer game experience. The survey was advertised via email to faculty and students of an Australian university, as well as via social media including Facebook and the official Xbox, PlayStation, Nintendo and Steam forums with a link provided for participants to share with friends. The survey consisted of two major parts.

Part 1: Participant Background

To establish background context to each participant's answers, demographic information regarding age, gender and competitive multiplayer game preferences was collected. Participants were also asked to rate their experience level playing competitive multiplayer video games on a numbered scale from 1 (not at all experienced) to 7 (extremely experienced). The use of "experience level" in opposition to asking for self-rated performance was chosen due to the potential variance in performance between different game genres. For example, while a participant may be a high-performing player in certain first-person shooter games, they may be low-performing in racing games and as such lower their self-reported performance rating.

Part 2: Effect of MDDA Framework Component Attributes on Player Experience

The earlier definition and explanation of multiplayer dynamic difficulty adjustment was provided to participants, as well as a description of the goal of these features in balancing challenge. One at a time, an explanation of a particular MDDA instance component was provided along with an example of its use in popular competitive multiplayer games *Mario Kart* and *Call of Duty: Modern Warfare 2*. Participants were asked to rate how the inclusion of differing MDDA instances would affect their player experience on a 7-point numbered scale ranging from "1 - very negatively" to "7 - very positively". All participants were asked to evaluate each MDDA attribute twice – first from the perspective of both a low-performing player (receiving assistance from the MDDA instance) and secondly from the perspective of a high-performing player (competing against the recipients of assistance from the MDDA instance). As a player's performance is relative to that of the other players in a match, they are likely to occupy the positions of both a low and high-performing player in different matches or games as their opponents vary. This makes it important to record the opinions of players from the perspective of both positions for within-groups comparison. Additionally, participants were asked for feedback on the framework, including any problems or suggestions for missing components or attributes.

Interview

Individual face-to-face interviews were conducted at Queensland University of Technology to probe player opinions on the MDDA Framework components and prior experience with MDDA in games they have personally played. Recruitment was conducted through local video game-related groups and societies in Brisbane, Australia. Participants were required to have played one or more competitive multiplayer games within the past 12 months, and each interview lasted between 20 and 50 minutes.

Interview questions were based around the same MDDA Framework components and attributes as the online survey, along with the same game examples. One at a time, each attribute was presented to the participant and they were asked how they 'feel' about MDDA instances with this attribute, as well as if they had encountered the attribute in any games they had played before. Interviews were semi-structured with participants prompted to provide reasoning behind their opinion and anecdotes where an MDDA instance of this type had been previously encountered. Suggestions for improvement or additions to the framework were also sought for further refinement.

Audio recordings and notes taken during each interview. For each framework component and attribute investigated, the reasoning behind a participant's positive or negative reaction was noted. Reasoning and concerns commonly expressed by multiple participants were then used to assist in the interpretation of the survey data by providing insights not able to be obtained through the examination of survey data alone.

RESULTS

Of the 154 valid participant responses to the survey collected, an average age of 23.70 (SD = 7.30) was recorded with 129 male and 32 female respondents. The interviews were conducted with 15 participants (10 male), 11 of whom were undergraduate students at Queensland University of Technology. Some survey participants did not complete all of the survey, in which case responses up to the last full page completed were included and any further incomplete responses removed, with 125 participants completing all pages of the survey.

Participants had first played a competitive multiplayer video games an average of 9.44 years ago and 91.56% had played within the last year. An average of 9.96 hours per week (SD = 9.20) was spent playing competitive multiplayer games by participants. First-person shooter games were the most popular genre for competitive multiplayer gameplay, played by 83.77% of those surveyed. Participants rated their experience level playing competitive multiplayer games an average of 5.28 (SD = 1.58) from '1 – not at all experienced' to '7 – extremely experienced'.

The following results explore survey participants' ratings of the effect of each component attribute on their player experience from 1 (very negatively) to 7 (very positively) from the perspectives of low and high performing players. For the purpose of clarity, results from the low-performing perspective will be abbreviated as LPP, and results from the high-performing perspective as HPP. Statistical analysis was conducted using a two-way repeated measures ANOVA, with the within-subjects factors of *component attribute* and *performance* and a dependent variable of *player experience* (operationalised as the participant's ratings of how the attribute would positively or negatively influence their experience playing the game). Significance was tested using Wilks' Lambda with an alpha of $p < 0.05$, with Bonferroni adjustment used for comparisons of *attribute* and *performance*. Mauchly's test of sphericity was used to confirm no violations of the assumption of sphericity were present, while skewness, kurtosis and residuals examination indicated normally-distributed data without outliers. Survey results are also displayed in graphs for each component with a y-axis scale of 3-5.5 to aid readability. Additional interpretation from interview participants is also noted for each framework component and individually indicated by participant codes N#. Finally, given debate regarding the suitability of parametric tests for surveys with number scales [16] all analyses were repeated with non-parametric tests and the pattern of results confirmed.

Component: Determination

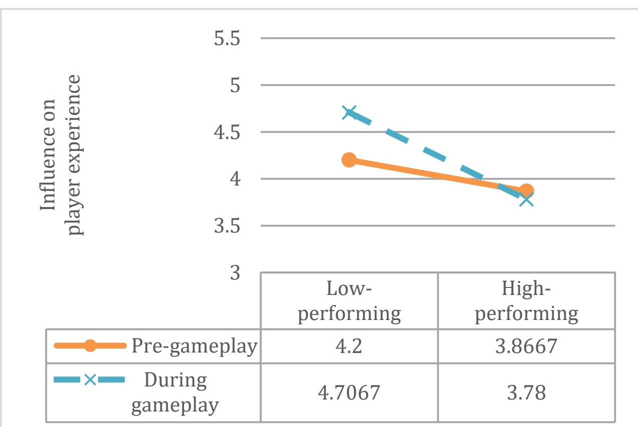


Figure 1. Influence of DETERMINATION on player experience

For the Determination component, there was a main effect for performance level as the attributes were rated higher from LPP (low-performing perspective) than HPP (high-performing perspective) ($F_{1,149} = 32.889$, $p < .001$, $\eta_p^2 = .181$). A main effect on attribute was also found ($F_{1,149} = 3.933$, $p = .049$, $\eta_p^2 = .026$), and these effects were qualified by a significant interaction between attribute and performance level on player experience ($F_{1,149} = 20.062$, $p < .001$, $\eta_p^2 = .119$) (see Figure 1). The Pre-Gameplay attribute was seen as having a more positive influence from LPP than HPP ($F_{1,149} = 6.512$, $p = .012$, $\eta_p^2 = .042$), with the same true for the During Gameplay attribute ($F_{1,149} = 54.186$, $p < .001$, $\eta_p^2 = .267$). The During Gameplay attribute was seen as having a more positive influence than the Pre-Gameplay attribute from LPP ($F_{1,149} = 15.613$, $p < .001$, $\eta_p^2 = .095$), while HPP did not distinguish between pre-gameplay and during-gameplay.

One participant commented that the Determination of an MDDA instance doesn't really matter to non-recipient (high-performing players) because "*the low-scoring guys are being helped anyway, so it doesn't matter when that's chosen if it's going to happen anyway*" (N8). Interview participants raised the point that performance is not always consistent between matches, with N12 indicated that low-performing players may prefer the MDDA to be enacted during gameplay "*because if you are having a really good day or you've gotten better, you still want the chance to win on your own skill*". Participants also highlighted the potential for reduced self-esteem from pre-gameplay MDDA, with N4 noting "*if you're already marked to be helped before the match starts it's like it's already telling you you're not good enough*".

Component: Automation

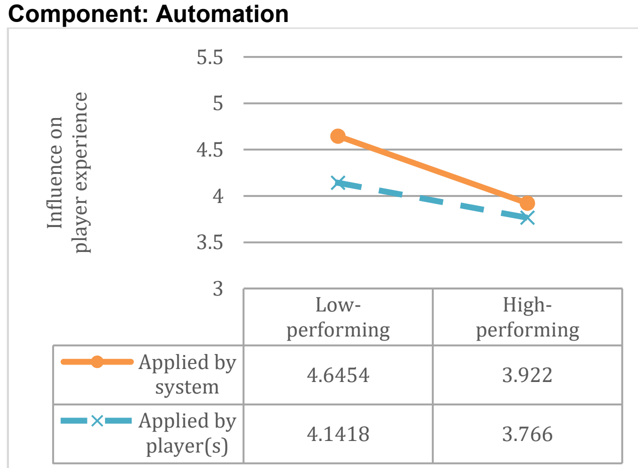


Figure 2. Influence of AUTOMATION on player experience

For the Automation component, there was a main effect for performance level as the attributes were rated higher from LPP than HPP ($F_{1,140} = 36.441$, $p < .001$, $\eta_p^2 = .207$). A main effect on attribute was also found ($F_{1,140} = 4.709$, $p = .032$, $\eta_p^2 = .033$), and these were qualified by a significant interaction between attribute and performance level on player experience ($F_{1,140} = 5.009$, $p = .027$, $\eta_p^2 = .035$) (see Figure 2). The Applied By System attribute was seen as having a more positive influence from LPP than HPP ($F_{1,140} = 43.733$, $p < .001$, $\eta_p^2 = .238$), with the same true for the Applied By Player(s) attribute ($F_{1,140} = 8.475$, $p = .004$, $\eta_p^2 = .057$). The Applied By System attribute was seen as having a more positive influence than the Applied By Player(s) attribute from LPP ($F_{1,140} = 9.014$, $p = .003$, $\eta_p^2 = .060$), while HPP did not distinguish between system or player applied.

Interview data suggests that MDDA applied by the system may be fairer than that applied by a player: the system may be "*more fair because it's not biased*" (N1); player assessment of the need for MDDA might "*not be accurate*" (N15); and some players may "*try to exploit it by giving* *themselves a boost so they can win*" (N1). N8 noted that these concerns are more applicable to online play against strangers, with the suggestion that "*if you're playing with your friends then it doesn't matter as much since you know the other guys*".

Component: Recipient

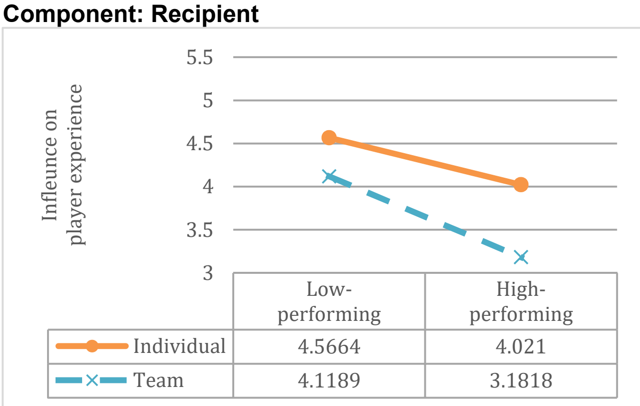


Figure 3. Influence of RECIPIENT on player experience

For the Recipient component, there was a main effect for performance level as the attributes were rated higher from LPP than HPP ($F_{1,142}$ = 44.03, p < .001, η_p^2 = .237). A main effect on attribute was also found ($F_{1,142}$ = 28.90, p < .001, η_p^2 = .169), and these effects were qualified by a significant interaction between attribute and performance level on player experience ($F_{1,142}$ = 7.75, p = .006, η_p^2 = .052) (see Figure 3). The Individual attribute was seen as having a more positive influence from LPP than HPP ($F_{1,142}$ = 24.816, p < .001, η_p^2 = .149), with the same true for the Team attribute ($F_{1,142}$ = 38.392, p < .001, η_p^2 = .213). The Individual attribute was seen as having a more positive influence than the Team attribute from LPP ($F_{1,142}$ = 12.425, p = .001, η_p^2 = .080), as well as HPP ($F_{1,142}$ = 31.406, p < .001, η_p^2 = .181), however the difference was more pronounced for high performing players.

Interview participants indicated a preference for MDDA applied to individual recipients. N2 framed the reasoning behind this as the desire to "limit any assistance to just the person who needs it" and avoid "boosting [the performance of] a whole team just because some players aren't as good". N4 stated: "if I was on a team and not doing very well, it would be embarrassing if my whole team got helped *because my score was bad*".

Component: Skill Dependency

For the Skill Dependency component, there was a main effect for performance level as the attributes were rated higher from LPP than HPP ($F_{1,133}$ = 21.230, p < .001, η_p^2 = .138). A main effect on attribute was also found ($F_{1,133}$ = 12.940, p < .001, η_p^2 = .089), and these were qualified by a significant interaction between attribute and performance level ($F_{1,133}$ = 29.567, p < .001, η_p^2 = .182) (see Figure 4).

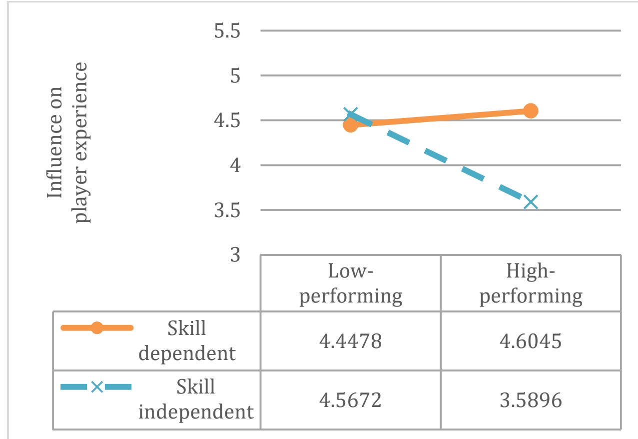


Figure 4. Influence of SKILL DEPENDENCY on player experience

The Skill Independent attribute was seen as having a more positive influence from LPP than HPP ($F_{1,133}$ = 55.858, p <.001, η_p^2 = .296) while LPP and HPP did not differ on the Skill Dependent attribute. The Skill Dependent attribute was seen as having a more positive influence than the Skill Independent attribute from HPP ($F_{1,133}$ = 45.670, p < .001, η_p^2 = .256), while in contrast LPP did not distinguish between the attributes.

Interview participants indicated that high-performing players may dislike skill independent MDDA. N2 commented that it "*might look a bit like cheating* [when] *someone's score gets better without them having to actually play any better*" with N15 adding that this might be more of an issue for "*eSports [professional players] and competitions or really serious players*".

Component: User Action

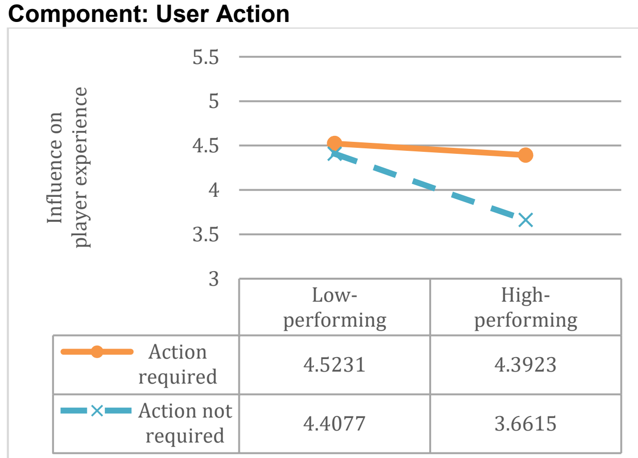


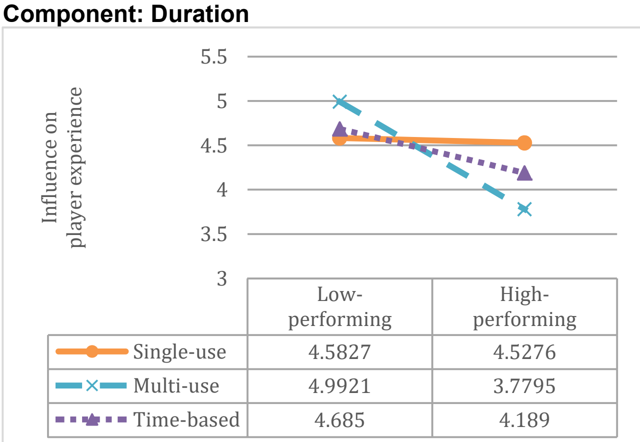
Figure 5. Influence of USER ACTION on player experience

For the User Action component, there was a main effect for performance level as the attributes were rated higher from LPP than HPP ($F_{1,129}$ = 23.969, p < .001, η_p^2 = .157). A main effect on attribute was also found ($F_{1,129}$ = 11.191, p =.001, η_p^2 = .080), and these were qualified by a significant interaction between attribute and performance level ($F_{1,129}$ = 17.222, p < .001, η_p^2 = .118) (see Figure 5). The Action Not

Required attribute was seen as having a more positive influence from LPP than HPP ($F_{1,129} = 43.912$, $p < .001$, $\eta_p^2 = .254$), while LPP and HPP did not differ on the Action Required attribute. The Action Required attribute was seen as having a more positive influence than the Action Not Required attribute from HPP ($F_{1,129} = 27.849$, $p < .001$, $\eta_p^2 = .178$) while LPP did not distinguish between these attributes.

Interview participant N1 commented that low-performing players might "*need to be helped anyway, so it should probably be automatic*". Other participants indicated that high-performing players may prefer user action be required, so that, for example "*the losing players can choose to not use it if they want to try and play just with skill instead*" (N12).

Component: Duration



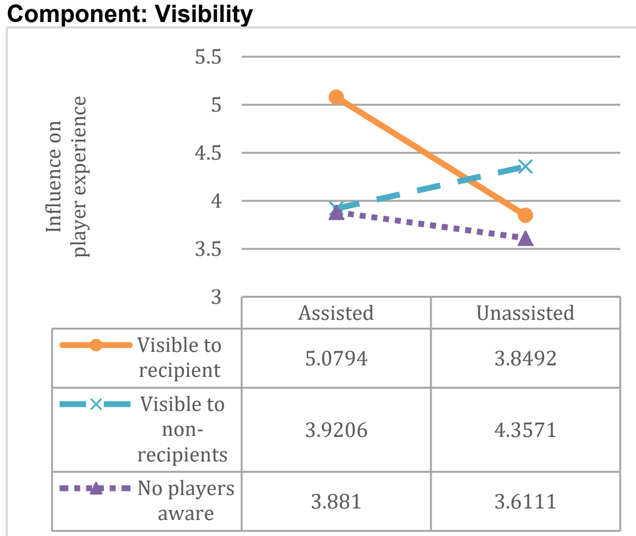
	Low-performing	High-performing
Single-use	4.5827	4.5276
Multi-use	4.9921	3.7795
Time-based	4.685	4.189

Figure 6. Influence of DURATION on player experience

Mauchly's test of sphericity indicated that the assumption of sphericity was met for attribute ($X^2(2) = 2.012$, $p = .366$) and the two-way interaction ($X^2(2) = 2.524$, $p = .283$). For the Duration component, there was a main effect for performance level as the attributes were rated higher from LPP than HPP ($F_{1,126} = 29.198$, $p < .001$, $\eta_p^2 = .188$), which was qualified by a significant interaction between attribute and performance level ($F_{2,252} = 36.008$, $p < .001$, $\eta_p^2 = .222$) (see Figure 6). The Multi-Use attribute was seen as having a more positive influence from LPP than HPP ($F_{1,126} = 70.603$, $p < .001$, $\eta_p^2 = .359$), with the same true for the Time-Based attribute ($F_{1,126} = 11.659$, $p = .001$, $\eta_p^2 = .085$). LPP and HPP did not differ on the Single-Use attribute. An effect was present for LPP ($F_{2,252} = 6.455$, $p = .002$, $\eta_p^2 = .049$) who saw the Multi-Use attribute as having a more positive influence than both the Single-Use ($p = .002$) and Time-Based ($p = .033$) attributes. An effect was also present for HPP ($F_{2,252} = 22.044$, $p < .001$, $\eta_p^2 = .149$) who saw the Single-Use attribute as having a more positive influence than the Multi-Use ($p < .001$) and Time-Based ($p = .011$) attributes, while Multi-Use was also seen as having a more positive influence than Time-Based ($P = .001$).

Interview participants indicated that low-performing players may prefer multi-use MDDA instances for the additional support provided in this context, e.g., "*they have a few chances to use it properly*" (N1). However, N1 also expressed that *"obviously low-performing would want that because there would be more performance gain, but the high-performing players might not like that since it gives more boosts"* and *"could provide too much assistance so winning doesn't take skill*". Participants also expressed concerns about players "gaming' multi-use MDDA, with N11 flagging that it may be *"more open to abuse and exploitation, like if someone purposely played badly to then get something they could use multiple times over the rest of the match to win*".

Component: Visibility



	Assisted	Unassisted
Visible to recipient	5.0794	3.8492
Visible to non-recipients	3.9206	4.3571
No players aware	3.881	3.6111

Figure 7. Influence of VISIBILITY on player experience

Mauchly's test of sphericity indicated that the assumption of sphericity was met for the two-way interaction ($X2(2) = 4.239$, $p = .120$), but not attribute ($X2(2) = 49.790$, $p < .001$) so Greenhouse-Geisser adjustment has been used with an epsilon of .751. For the Visibility component, there was a main effect for performance level ($F_{1,125} = 17.104$, $p < .001$, $\eta_p^2 = .120$) as the attributes were rated higher from LPP than HPP. A main effect on attribute was also found ($F_{1.503,187.870} = 10.236$, $p < .001$, $\eta_p^2 = .076$), and these were qualified by a significant interaction between attribute and performance level ($F_{2,250} = 47.005$, $p < .001$, $\eta_p^2 = .273$) (see Figure 7). The Visible to Recipient attribute was seen as having a more positive influence from LPP than HPP ($F_{1,125} = 79.362$, $p < .001$, $\eta_p^2 = .388$), with the same true for the Not Visible attribute ($F_{1,125} = 5.056$, $p = .026$, $\eta_p^2 = .039$). However, the Visible to Non-Recipients was seen as having a more positive influence from HPP than LPP ($F_{1,125} = 10.384$, $p = .002$, $\eta_p^2 = .077$). An effect was present for LPP ($F_{1.631,203.887} = 28.078$, $p < .001$, $\eta_p^2 = .183$) who saw the Visible to Recipient (themselves) attribute as having a more positive influence than both the Visible to Non-Recipients ($p < .001$) and Not Visible ($p < .001$) attributes. An effect was also present for HPP ($F_{1.720,215.010} = 8.956$, $p < .001$, $\eta_p^2 = .067$) who saw the Visible to Non-Recipient (themselves) attribute as having a more positive influence than both the Visible to Recipients (p = .005) and Not Visible (p = .002) attributes.

One participant commented that as a low-performing player, "*I would want to be told if I was being helped so I know that it's not just my skill*" (N6) while another stated "*I would probably be able to use it better if I knew what the assistance was*" (N9). However, they also noted that these players may not wish it to be visible to high-performing players for a range of reasons: "*that would make me a target and they'd probably try to hunt me down*" (N9); "*it would be really satisfying to take them down*" (N11); "*if I saw someone being helped I'd probably avoid them*" (N5).

Framework Suggestions and Refinements

A small number of survey and interview participants raised that players may become aware of the presence, effects or recipients of an MDDA instance even if not visible, with some citing games such as *Mario Kart* (where the algorithm for item selection is never shown to players). Conversely, others mentioned the possibility that a player may not become aware of an MDDA instance even though it is visible in the game (using examples include *Call of Duty* death streaks). This brought into question the validity of the Visibility component, which is discussed below.

DISCUSSION

When players of competitive multiplayer games were questioned on the effect different MDDA component attributes would have on their play experience, a general trend emerged. Participants reported an expectation that almost all forms of MDDA would have a more positive effect on the experience of low-performing players than high-performing players. As the presence of MDDA instances most often provides a performance benefit to low-performing players, this result was not surprising.

The effects on player experience reported by the participants reveal three major themes or patterns in responses across multiple attributes:

A. Player control over the instance.
B. Personal benefit from the effects of the instance.
C. Awareness of the instances' presence and effects.

These themes provide insight into the values of players for the purpose of enabling a player-centric approach to designing and implementing MDDA instances, as well as highlighting the conflicts between the likely impacts on the player experience of low and high performing players.

A. Player Control

A trend across the four components of Duration, Skill Dependency, and User Action provides an indication that when high-performing, players would prefer increased control over the presence, action and properties of the MDDA instance.

From the perspective of a high-performing player, participants reported a more positive experience for instances that are *skill dependent* with *user-action required* and only *single-use*. Each of these component attributes increase the control of the player over the assistance provided through increasing reliance on the player to make effective use of the opportunity for assistance. Through the combination of these preferences, the player would have one opportunity (single-use and skill dependent) to receive assistance at a time of their choosing (user action). A result of implementing these preferences would be increased transparency of the presence and mechanics of the MDDA instance to the players in order for the increased control to be possible. However, when taking the perspective of a low-performing player receiving performance assistance from the MDDA instance, participants did not demonstrate as much inclination for increased player control as evidenced by the lack of difference in preference for the attributes of Skill Dependency or User Action. When paired with the responses of interview participants, these results indicate players desire to still play the primary role in performance when in the position of a high-performing player. In contrast, when taking the perspective of a low-performing player, they are not as concerned by their degree of player control or the role of skill in their performance using MDDA.

Participants agreed on one particular component affecting control for both low and high-performing players: players preferred the need for activation of an MDDA instance to be automated by the game system rather than chosen by players. Interview participants noted the potential for MDDA features to be exploited or abused by players motivated by the potential performance assistance. The use of an automated game system was viewed as more impartial than relying on players to accurately judge the need for MDDA and less open to exploitation. Consequently, Automation is the only component in which participants preferred lesser control over the MDDA instance.

Additionally, the higher rating of system-automated instances from the perspective of low-performing players than high-performing is reflective of comments by interview participants concerning the effect of MDDA on pride. Participants indicated that low-performing players may experience social embarrassment when MDDA assistance is applied to them by other players. Similarly, applying MDDA assistance to oneself may be seen as an acknowledgement of lower skill or 'ranking' amongst the players or draw unwanted attention compared to the game system automating the process.

B. Personal Benefit

Trends were found between attributes that may affect the degree of personal benefit received for the Duration, Recipient, Skill Dependency and Visibility components. From the low-performing perspective, players were more likely to report a positive effect on enjoyment from component attributes that may provide more personal benefit to the recipient (e.g., the multi-use option for the Duration attribute, as opposed to only single-use or time-based). However, a more positive effect was reported from a high-performing player's perspective for attributes which could allow high-performing players to minimize or nullify its effects. For example, an MDDA instance made visible to non-recipients would allow high-performing players to adapt to, target or take advantage of a low-performing player marked as being assisted.

Together, this paints a picture of players valuing MDDA instances that allow them the most potential performance benefit or least performance loss. However, the more positive response to attributes that may minimize the benefits to low-performing players from the perspective of a high-performing players runs contradictory to the intent of MDDA in balancing player performance. As a balance between task difficulty and player ability have been thoroughly demonstrated as key factors in achieving flow [8] and a sense of competence as key for intrinsic motivation [19], this may indicate an area in which player preferences do not match the player experience in practise. Consequently, when placing complete faith in players' abilities to align preferences with optimal experience there is a risk of players unintentionally harming their own experience in the pursuit of improved performance and increased chances of 'winning'. Testing of balancing in a multiplayer first-person shooter game by Vicensio-Moreira, Mandryk and Gutwin [23] confirmed this possibility, with the most positive experience noted by both low and high-performing players when performance was most balanced in spite of the negative effect on the stronger player's score.

C. Player Awareness

The Visibility component provided mixed results between the perspectives of low and high-performing players with differing attributes reported as having a positive effect on enjoyment. From both perspectives, the preferred attribute was that which would give them personal awareness of the presence or effects of the MDDA instance in that role. As low-performing players (the recipients), MDDA visible to recipient was seen more positively; an expected result to allow the recipient of assistance to potentially make better use of the performance enhancement. Similarly, viewed as high-performing players (non-recipients), MDDA visible to non-recipients was rated higher which echoes the values for personal benefit. This may be due to a sense of fairness through better knowledge of MDDA, but also provide the opportunity to adjust strategy to compensate for its effects.

Combined with interview responses, it is very clear that players do not wish for MDDA to be 'hidden' from view when they are playing. However, survey participants expressed a lower preference for MDDA to be visible to *other* players in the match. That is, from the low-performing perspective players did not indicate a positive effect on their experience when non-recipients were aware, while from the high-performing perspective players did indicate a positive effect if recipients were aware. Again, this suggests a bias towards the attributes with the greatest potential to maintain or improve one's own performance; supported by the need for feelings of competence [20].

Gerling and colleagues [13] suggest these preferences may not reflect an optimal experience, as visibility of balancing may weaken an assisted player's internal attribution of success through the perception that their ability alone was not responsible. In contrast, Depping and colleagues [11] found disclosure of skill assistance to not have negative effects as players may still internally attribute success when assisted, and attribute reduced performance to the balancing system when competing against assisted players. These conflicting views highlight the potential for player preferences to differ from actual gameplay experience, and the need for further research to examine these effects.

REFINEMENT TO MDDA FRAMEWORK

As described above, our findings highlight that the component of visibility does not account for whether or not a player is aware of a particular MDDA instance (regardless of its visibility). As a result, the framework would not be able to account for cases in which players can be aware of a technique that is not intentionally communicated to them, and similarly situations in which a player does not notice or correctly interpret a technique that is made visible.

In response to the feedback and recognition of the issue, Visibility was removed from the framework in favour of a new 'Awareness' component. This component indicates a player's awareness of the MDDA instance's effects on gameplay and recipients. Unlike the other attributes, Awareness is subjective and measured during or post-play rather than defined prior to activation of the technique. A player's degree of awareness may be affected by their experience with the game, understanding of its mechanics and the MDDA instance's implementation.

A player's initial awareness of the presence of an MDDA instance is binary, as they either know of the existence of the MDDA in the match or not. Their degree of awareness of the effects and recipients of the MDDA is then represented by a two-axis matrix (see Figure 8). The horizontal 'x' axis displays the continuum of a player's awareness of the effects of the MDDA (i.e., how

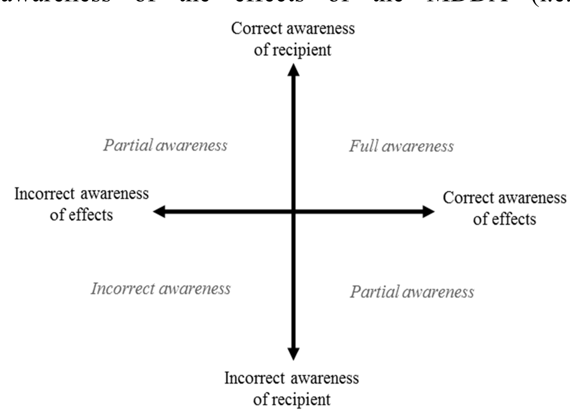


Figure 8. Awareness component matrix

performance is manipulated such as providing control assistance or a score modifier). This extends from an incorrect awareness (player is wrong about the effects), to correct awareness of the effects. The vertical 'y' axis represents awareness of the recipient of the MDDA's effects, ranging from incorrect (believes player(s) are being assisted when they are not or vice versa) to a correct identification of the recipient(s). Together, these allow player awareness to be mapped and represented independently of designer intentions of MDDA.

ADDITIONAL DESIGN CONSIDERATIONS

Along with the identified player values of *player control*, *personal benefit* and *player awareness*, survey and interview responses suggest several further considerations and for designers to contemplate when implementing MDDA features. As these are based on examination of player expectations, it is important to note actual effects in gameplay may differ.

Transparency

A concern of participants was the potential for MDDA to be seen as "cheating", particularly by the high-performing players. Combined with the preferences of participants for component attributes that increase transparency, designers should consider ensuring the presence of MDDA in their game is clearly communicated; even if when and to whom it is applied in gameplay is not visible. This may help players to view the MDDA instance like any other game mechanic rather than as 'under-the-table' interference by the designer in competitive play. Similarly, this can also help avoid a potential situation in which highly-experienced players become aware of MDDA through their own deeper understanding of the game mechanics, placing inexperienced players at a greater disadvantage.

The role of skill in match outcomes

While absolute matched challenge or performance between players may appear to be the ultimate goal in theory, the benefits to player experience may be undone by the competitive and social aspect of multiplayer games. With concerns expressed by players about the potential exploitation for performance gain and 'strength' of the MDDA effects, designers may wish to avoid assisting low-performing players to the point of completely matched performance. This can have the effect of decreasing or nullifying the contribution of skill to match outcomes, reducing gratification and intrinsic motivation to continue playing for both low and high-performing players [17].

One size does not fit all

As the results have demonstrated there can be conflicts between the perspectives of low and high-performing players. By the nature of competitive multiplayer, fulfilling these preferences for low-performing players (the recipient of assistance from MDDA instances) can conflict with the preferred play experience for the high-performing players competing against them due to the value of *personal benefit*. While the intent of balancing challenge remains, the responses collected indicate potentially conflicting player experience effects. When designing MDDA features, it may therefore be prudent to assess and target the performance demographic most in need of the benefits of improved player experience from MDDA. For example, if an identified issue is high-performing players leaving a particular game, MDDA implementation may be weighted with the component attributes most valued by these players. In this case, a designer may seek to improve *player awareness* and *personal benefit* for high-performing player through using the 'visible to non-recipients' attribute of the Visibility component. Similarly, if designing to appeal to new players, MDDA features may be weighted towards improving *personal benefit* for low-performing players such as the 'multi-use' Duration attribute.

LIMITATIONS AND FUTURE WORK

While examination of player expectations regarding MDDA is valuable for understanding how players may perceive their use in games, it is important to consider the potential inaccuracy of participants' judgement of their play experiences as a limitation of this study. For example, from the perspective of low-performing players, survey respondents indicated MDDA visible to the recipient (themselves) to have a positive influence on their experience. However, other game balancing research found a negative effect on self-esteem and feelings of relatedness when low-performing players are aware [12]. It is suspected that the conflicts between the perspectives of low and high-performing players may be the result of players incorrectly predicting their own play experience. Future research is needed to determine if and where player expectations conflict with the actual resulting experience. Additionally, a gender imbalance was present in this study's sample which may influence the results.

CONCLUSION

The survey and interviews were conducted to evaluate player preferences and the expected player experience associated with differing implementations of MDDA. Using the MDDA Framework [2], the effects of different components were individually investigated and interpreted to allow for an understanding of player preferences for MDDA implementation and design. By determining the values consistent across players such as player control, personal benefit and player awareness, designers can better tailor their implementation of MDDA to improve the appeal of their games. Additionally, using the perspectives of both a low-performing player receiving MDDA assistance and a high-performing player competing against assisted players allowed for the identification of conflicting effects where opinions vary as a function of performance level. In response to player feedback regarding the MDDA Framework and the identification of the subjectivity of awareness, the Visibility component was removed from the framework and replaced with a new Awareness component. This has further strengthened the ability of the framework to accurately classify and differentiate MDDA instances.

REFERENCES

1. Gustavo Andrade, Hugo Santana, and Bôite Place Jussieu. 2005. Challenge-Sensitive Action Selection : an Application to Game Balancing Vincent Corruble. *Proceedings of the 2005 IEEE/WIC/ACM International Conference on Intelligent Agent Technology (IAT'05)*.
2. A. Baldwin, D. Johnson, P. Wyeth, and P. Sweetser. 2013. A framework of dynamic difficulty adjustment in competitive multiplayer video games. *Proceedings of the IEEE International Games Innovation Conference*.
3. Alexander Baldwin, Daniel Johnson, Peta Wyeth, and Penny Sweetser. 2013. A framework of dynamic difficulty adjustment in competitive multiplayer video games. *IEEE Consumer Electronics Society's International Games Innovations Conference, IGIC*: 16–19. http://doi.org/10.1109/IGIC.2013.6659150
4. Scott Bateman, R.L. Mandryk, Tadeusz Stach, and Carl Gutwin. 2011. Target assistance for subtly balancing competitive play. *Proceedings of the 2011 annual conference on Human factors in computing systems*, ACM, 2355–2364.
5. Jared E. Cechanowicz, Carl Gutwin, Scott Bateman, Regan Mandryk, and Ian Stavness. 2014. Improving player balancing in racing games. *Proceedings of the first ACM SIGCHI annual symposium on Computer-human interaction in play - CHI PLAY '14*: 47–56. http://doi.org/10.1145/2658537.2658701
6. Oscar Clark. 2014. *Games As A Service*. Focal Press, Burlington. http://doi.org/10.4324/9781315849102
7. Delwin Clarke and P Robert Duimering. 2006. How computer gamers experience the game situation: a behavioral study. *Computers in Entertainment* 4, 3: 6. http://doi.org/http://doi.acm.org/10.1145/1146816.1146827
8. Mihaly Csikszentmihalyi. 1990. *Flow: The Psychology of Optimal Experience*. Harper & Row. http://doi.org/10.1145/1077246.1077253
9. Edward L Deci and Richard M Ryan. 1985. *Intrinsic motivation and self-determination in human behavior*. Plenum Press, New York.
10. Alena Denisova and Paul Cairns. 2015. Adaptation in Digital Games: The Effect of Challenge Adjustment on Player Performance and Experience. *Proceedings of the 2015 Annual Symposium on Computer-Human Interaction in Play - CHI PLAY '15*, January: 97–101. http://doi.org/10.1145/2793107.2793141
11. Ansgar E Depping, Regan L Mandryk, Chengzhao Li, Carl Gutwin, and Rodrigo Vicencio-moreira. 2016. How Disclosing Skill Assistance Affects Play Experience in a Multiplayer First - Person Shooter Game. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, ACM.
12. Kathrin M. Gerling, Matthew Miller, Regan L. Mandryk, Max Valentin Birk, and Jan D. Smeddinck. 2014. Effects of balancing for physical abilities on player performance, experience and self-esteem in exergames. *the 32nd annual ACM conference*, 2201–2210. http://doi.org/10.1145/2556288.2556963
13. Kathrin M. Gerling, Matthew Miller, Regan L. Mandryk, Max Valentin Birk, and Jan David Smeddinck. 2014. Effects of balancing for physical abilities on player performance, experience and self-esteem in exergames. *Proceedings of the 32nd annual ACM conference on Human factors in computing systems - CHI '14*: 2201–2210. http://doi.org/10.1145/2556288.2556963
14. Ralf Herbrich and Thore Graepel. 2006. TrueSkillTM: A bayesian skill rating system. *Microsoft Research*.
15. Robin Hunicke and Vernell Chapman. 2004. AI for dynamic difficulty adjustment in games. *Challenges in Game Artificial Intelligence AAAI*: 91–96. http://doi.org/10.1145/1178477.1178573
16. Susan Jamieson. 2004. Likert scales: How to (ab)use them. *Medical Education* 38, 12: 1217–1218. http://doi.org/10.1111/j.1365-2929.2004.02012.x
17. Snezhanka Kazakova, Veroline Cauberghe, Mario Pandelaere, and Patrick De Pelsmacker. 2014. Players' expertise and competition with others shape the satisfaction of competence needs, gaming gratifications, and contingent self-esteem in a gaming context. *Cyberpsychology, behavior and social networking* 17, 1: 26–32. http://doi.org/10.1089/cyber.2012.0413
18. C Pedersen, J Togelius, and G N Yannakakis. 2009. Modeling Player Experience in Super Mario Bros. *IEEE Symposium on Computational Intelligence and Games, 2009.*, 132–139.
19. Richard M Ryan, C Scott Rigby, and Andrew Przybylski. 2006. The motivational pull of video games: a self-determination theory approach. *Motivation and Emotion* 30, 4: 347–363. http://doi.org/10.1007/s11031-006-9051-8
20. Richard M. Ryan, C Rigby, and Andrew Przybylski. 2006. The Motivational Pull of Video Games: A Self-Determination Theory Approach. *Motivation and Emotion* 30, 4: 344–360. http://doi.org/10.1007/s11031-006-9051-8
21. B Schölkopf, J Platt, and T Hofmann. 2007. TrueSkill^{TM}: A Bayesian Skill Rating System. *Advances in Neural Information Processing Systems*: 569–576. Retrieved January 23, 2013 from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6287323

22. Penelope Sweetser and Peta Wyeth. 2005. GameFlow: a model for evaluating player enjoyment in games. *Computer Entertainment* 3, 3: 3–24. http://doi.org/10.1145/1077246.1077253

23. Rodrigo Vicencio-Moreira, Regan L. Mandryk, and Carl Gutwin. 2015. Now You Can Compete With Anyone: Balancing Players of Different Skill Levels in a First-Person Shooter Game. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI '15*: 2255–2264. http://doi.org/10.1145/2702123.2702242

24. Haiyan Yin, Linbo Luo, Wentong Cai, Yew-soon Ong, and Jinghui Zhong. 2015. A Data-driven Approach for Online Adaptation of Game Difficulty. 146–153.