Understanding players to enhance their fun: how to extract player data and motivation factors for procedural content generation

Leonardo Tórtoro Pereira[1], Kamila Rios da Hora Rodrigues[2], Claudio Fabiano Motta Toledo[2], T. Yuji Teoi[2]

[1]Instituto de Geociências e Ciências Exatas
Universidade Estadual Paulista (UNESP) - Rio Claro, SP - Brasil

[2]Instituto de Ciências Matemáticas e de Computação
Universidade de São Paulo (USP) - São Carlos, SP - Brasil

leonardo.t.pereira@unesp.br, kamila.rios@icmc.usp.br,
yujiteoi@gmail.com, claudio@icmc.usp.br

Abstract. *This paper uses results from recent literature on player data collection and Human-Computer Interaction (HCI) fundamentals to classify the data collected by gaming systems to identify different types of players and their motivators. Our study proposes to address the lack of standards and ambiguous identification of data and collection techniques, which hinders progress in the Procedural Content Generation field. Our proposed classification may help researchers and game developers build metrics to evaluate users' motivators and player types, fostering the chance to generate game content to optimize performance, fun, and user satisfaction when playing.*
Keywords *Player Modeling, Player Behavior, User Profiling, Digital Games, Procedural Content Generation.*

1. Introduction

Understanding the different types of players and creating games that appeal to as many people as possible is one of the challenges of the multibillion-dollar game industry [Lora et al. 2016]. Another challenge is the game's difficulty adjustment. One technique to address these challenges is Procedural Content Generation (PCG), which can automatically create different types of game content through algorithms.

Another set of important techniques are those that lead to the extraction of player data and its analysis to define player profiles, the player's skill level, and their main motivation factors to retain their interest in a game. They often turn the game development process into a user-centered design approach [Loria e Marconi 2018, Melhart et al. 2019].

If it can adequately model a player's preferences, this model can feed a PCG algorithm for a given game. If fed back with the evolution of the player's performance in each new game, we can create a system capable of motivating any player to continue playing it for more time and keeping them entertained and challenged.

However, the scientific literature has gaps to be surpassed to get closer to this type of system. One of these is the lack of PCG algorithms able to adapt their content in real-time. Bicho and Martinho [Bicho e Martinho 2018] propose one, but for a particular setting. We argue that the lack of standards for collecting player data harms the precision for identifying the player type and, consequently, content adaptation in PCG systems.

Here, we classify the explicit data collection necessary to create player profiles and individual player models. Our proposed categorization of data collection relates significantly to Jameson's categories for collecting data for "Adaptive Interfaces and Agents", for information explicitly provided by users to the system [Jacko 2012, p. 318]. They use techniques to adapt interfaces based on data collected from users with Artificial Intelligence, similar to content adaptation in PCG algorithms.

2. Explicit Self-Reports and -Assessments

The explicit self-reports and -assessments involve data explicitly provided by the user when answering questionnaires. It may define users' demographic group, interests, knowledge of a certain subject, opinion on items and actions taken, among other topics.

This type of self-report aims to gather information about the user's objective properties (such as age, profession, and housing), often relevant to determining their knowledge and interests. Once performed, it does not need to be collected again.

It is commonly collected from questionnaires mixed with self-assessment questions about generic dimensions. An example can be seen in Heijne's demographic questionnaire and in the work of Ferreira and Toledo, who, in addition to demographic data, collect information on game time, console preference, game genre preference, among others [Heijne e Bakkes 2017, Ferreira e Toledo 2018].

Some studies use personality tests (or modified versions) to identify player profiles and correlate them to gameplay habits. De Lima, Feijó, and Furtado [de Lima et al. 2021] created a method for adapting procedurally generated branching quests in real-time, according to players' actions and preferences. They integrated a short version of a *Big Five personality traits test* (OCEAN) in a 2D RPG, and answers were used as input for a neural network, to classify player preferences for quest decisions. The player preferences are used as a component to adapt procedurally generated branching quests. Haijne's work [Heijne e Bakkes 2017] did a modified OCEAN model to relate personality to gameplay elements.

Moreover, collecting more elaborate data, such as occupation or place of residence, may require tedious interactions in menus or typing text. If excessive data is requested, some users may be concerned about their privacy and decide not to continue the experiment. We suggest collecting only the information necessary for the system, explaining to users how their data will be used [Jacko 2012, p. 318].

2.1. Self-assessments of interests and knowledge: Motivation and Player Type Questionnaires

This type of self-assessment collects data about the player's position on a particular general dimension, such as their interest or knowledge about a certain topic, or the importance they give to a specific evaluation criterion. The assessment must be concise to avoid misrepresenting the authentic player's position, which may be problematic in sensitive topics [Jacko 2012, pp. 318–319]. To this end, the anonymity of an online questionnaire is welcome, and clear questions with well-defined points on the Likert scale.

In gaming research, self-assessments of interests and knowledge questionnaires usually inquire about a player's gaming experience, often through scaled questions like "*What is your gaming experience*" or "*How many hours do you play per week*". This may extend to questions about game genres, the game used in testing, or the gaming platform.

For example, Heijne and Sander [Heijne e Bakkes 2017] and Ferreira and Toledo [Ferreira e Toledo 2018] use this approach to analyze the correlation between gaming experience and various gameplay factors observed and subsequently measured in questionnaires, such as opinions about difficulty and performance in different scenarios, or to analyze whether experience with games influences the player's ability to differentiate levels generated by humans from those generated by computers. Likewise, Rivera-Villicana *et al.* [Rivera-Villicana et al. 2018] asks such questions, however, to create a *Belief-Desire-Intention* (BDI) player model.

The work of Vahlo *et al.* [Vahlo et al. 2017] conducts a questionnaire on player preference regarding 33 core game dynamics, drawn from the authors' analysis of 700 game reviews. All questions are answered on a 7-item Likert scale and were used to group respondents into 7 groups, based on game dynamics preferences [Vahlo et al. 2017].

Finally, Pereira *et al.*'s research uses a content orchestrator (i.e., an algorithm to generate more than one content procedurally) and tests the generated content's opinion of a control and test group, based on the player's profile. They used an adapted version of Yee and Ducheneaut's player motivation profiles, using a short questionnaire to define the player's profile before playing. Then, their system generated the content matching the player's profile for the test group, or matching another profile for the control group. Their results indicate that players with content matching their profile had a more positive opinion. This suggests that PCG algorithms may be better received when adapting content for different profiles, but these profiles must be identified correctly [Pereira et al. 2024].

2.2. Self-reports on specific evaluations - Content Validation

This type of self-report collects information about the user's explicit evaluation of specific items, related to items they have direct experience with (e.g., the game they are playing), actions they have just performed, items they need to judge based on the description, or the name of an item with which the user has had experience in the past. The physical action to answer is usually a click on the mouse, however, some inference or memory retrieval may be required for some questions. As users typically do not like to make explicit assessments that are not directly related to their task, it is ideal that the questions are as objective as possible and of a reduced size [Jacko 2012, p. 319].

In research on games, it is common to have questionnaires about the player's opinion on gameplay issues, how fun or difficult they found the game or certain segments, and even whether that content was generated by a human being or an algorithm, as in *Player Experience of Needs Satisfaction* (PENS) [Ryan et al. 2006], *Game Experience Questionnaire* (GEQ) [Poels et al. 2007], *Game Engagement Questionnaire* [Brockmyer et al. 2009], *Ubisoft Perceived Experience Questionnaire* (UPEQ) [Azadvar e Canossa 2018] and *Player Experience Inventory* (PXI) [Abeele et al. 2020]. The UPEQ specifically was used in other research to create successful models for predicting user motivation [Melhart et al. 2019].

The questionnaires above relate questions to constructs (e.g., Consequences, Flow, Fun, etc.), defined by experts in the areas of Game Design or Game User Research. Except for the Game Engagement Questionnaire, they base their constructs (at least partially) on scientific theories from different areas, with the PXI being based on the *Means-end Chain Theory* from Marketing, and the PENS, GEQ, and UPEQ on the *Self-Determination Theory* (SDT) from Psychology.

Recent studies in PCG applied questionnaires for content evaluation. Hojatoleslami, Zamanifar, and Zamanifar [Hojatoleslami et al. 2024] used the *Game Experience Questionnaire* to evaluate a procedurally generated dungeon and its game atmosphere. Pereira, Viana, and Toledo [Pereira et al. 2021] and Pereira *et al.* [Pereira et al. 2024] evaluated the content generated by a PCG system asking players about the content's fun, difficulty, and if it seemed human-made. They also compared if the content adapted for the player's profile was better received than unadapted content.

3. Findings summary and comparison

Table 1 summarizes the previously presented classification of explicit self-reports and -assessments.

Tabela 1. Comparison of Explicit Self-Reports and -Assessments.

	Collection Frequency	Need for Anonymity	Collection of Personal Data	Use of Personality Tests	Use of Players' Profile Tests	Evaluation of Specific Constructs	Evaluation of Player Experience	Evaluation of Players' Opinion about a Content
Demographic Questionnaire	LOW	✓	✓	✓	X	X	X	X
Motivation and Player Type Questionnaire	LOW	X	X	X	✓	✓	✓	X
Content Validation	HIGH	X	X	X	X	✓	✓	✓

Next, Table 2 compares how each reviewed study collects data, and for what purpose it's used. Some used demographic questionnaires [Ferreira e Toledo 2018, Loria e Marconi 2018, Heijne e Bakkes 2017], others used motivation and player type questionnaires [Pereira et al. 2024, de Lima et al. 2021, Melhart et al. 2019, Ferreira e Toledo 2018, Heijne e Bakkes 2017]. Others used content validation questionnaires [Pereira et al. 2024, Hojatoleslami et al. 2024, Pereira et al. 2021].

Most works used player-type questionnaires. They often used this data to validate a PCG algorithm [Pereira et al. 2024, Hojatoleslami et al. 2024, Pereira et al. 2021, Melhart et al. 2019, Ferreira e Toledo 2018, Heijne e Bakkes 2017]. Some adapted content based on the player profile [Pereira et al. 2024, de Lima et al. 2021, Heijne e Bakkes 2017], and a few modeled players [Pereira et al. 2024, Loria e Marconi 2018].

Tabela 2. Comparison of selected PCG studies that collect user data.

	Demographic Questionnaire	Motivation and Player Type Questionnaires	Content Validation	Validation of PCG Algorithm	Content Adaptation from Player Profile	Player Modeling
[Pereira et al. 2024]	X	✓	✓	✓	✓	✓
[Hojatoleslami et al. 2024]	X	X	✓	✓	X	X
[Pereira et al. 2021]	X	X	✓	✓	X	X
[de Lima et al. 2021]	X	✓	X	X	✓	X
[Melhart et al. 2019]	X	✓	X	✓	X	X
[Ferreira e Toledo 2018]	✓	✓	X	✓	X	X
[Loria e Marconi 2018]	✓	X	X	X	X	✓
[Heijne e Bakkes 2017]	✓	✓	X	✓	✓	X

4. Conclusion

Despite the great interest in creating player profiles that have a direct correlation with each player's playing style, especially in the area of *online* content adaptation (focused on the algorithmic *design* of user-centered content), few studies in the literature attempt to obtain empirical results on these profiles, whether through questionnaires and theoretical models, or through the grouping of metrics collected during matches. And fewer attempted to adapt PCG algorithms to different players.

In this paper, we classified three types of explicit evaluations based on concepts of the HCI field: Demographic Questionnaire, Motivation and Player Type Questionnaires, and Content Validation. This proposed classification may help guide authors toward a common nomenclature in player modeling approaches in PCG algorithms.

For future work, we aim to propose and validate a set of questionnaires for each type of classified evaluation, focusing on player modeling and PCG applications. Thus, promoting discussion for better data collection in player modeling and PCG content adaptation fields, and providing a template for others to follow.

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