Personalizing Game Selection for Mobile Learning
With a View Towards Creating an Off-line Learning Environment for Children

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Abstract: Online education nowadays plays a very important role in enhancing the educational processes mostly for adults. Given this maturing technology and the number of children that lack access to safe education, mobile education for children is a logical next step and opens options that change their prospects. This paper is part of a larger project on mobile learning with games for children without access to schools. Games can motivate children to learn without the necessity of a teacher. The goal is to recommend learning games based on children's preferences of past choices and ratings, which can supplement other recommender systems. The resulting implemented algorithm is designed as a plug-in to exisiting learning platforms that use games. Such a system was implemented and evaluated in a feasibility study on adults. We show that a prediction based on user's choice and rating of games corresponds to a direct survey to determine the gamer types in 66% of the cases for 61 participants.

1 INTRODUCTION

At the beginnings of the 21st century the E-learning concept emerged uncovering many opportunities (Bullen, 2003) of providing quality education for the unfortunate and filling the gaps in our pre-existing educational systems. Such gaps include and are not limited to accessibility to educational facilities and materials as well as personalization and customizability of the educational process. While some integrated this breakthrough in their old systems others did not and maintained the classical way of educating students.

E-learning faces many criticisms such as the lack of human interaction, absence of standards and the ambiguity of the information delivery process (Tavangarian et al., 2004). But E-learning was introduced as a solution to expand our educational reach and limits, rather than a way of replacing traditional education.

With the advent of MOOCs (Massive Open Online Courses) the educational landscape has changed once again to render education independent of geography. These courses are primarily geared towards adults; few courses on edX and Coursera are addressing children or adolescents. Khan academy (Thompson, 2011) also offers a platform for learning, not community based but addressing children specifically. The platforms are generally not adaptive and additionally struggle with issues of retention and motivation (Khalil and Ebner, 2015).

Our goal is to provide a mobile platform geared towards providing an education for children at the elementary years regardless of their location, keeping in mind minimal technological and logistic constraints (Berkling et al., 2016). Since it is assumed that teachers are not available, the education must be self-motivating. We therefore propose games, the oldest way to learn, to be used as a vessel for learning chunks of content leveled according to the common core standards (National Governors Association Center for Best Practices, 2010). To quote James Paul Gee, "Learning is for nearly all good games a core mechanic" (Steinkuehler et al., 2012, p. xvii).

In this work we study the art of personalizing the educational process and educational games by studying how to provide "The right game, for the right student, at the right time". While recommender systems tend to look at external factors (Felfernig et al., 2013), we look at internal characteristics specific both to games and users. This system can then be used jointly with other proven recommender systems. Various psychological and gamification concepts are analyzed in order to study their application towards building an educational environment suitable for each student. Having selected one of the models, a system

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is implemented and evaluated. In a feasibility study the evaluation takes place on adults who share motivations with children for gaming (Yee, 2006a).

Chapter 2 explores a number of learning and personality styles and analyses their usefulness for the application of interest. Chapter 3 describes the methodology used in the preliminary study for a chosen model. Chapter 4 will evaluate the results, followed by a critical discussion and conclusions in Chapter 6.

2 THEORETICAL BACKGROUND

In this section, researched learning styles, followed by personality types and finally, gaming styles are reviewed. The models were examined with respect to their suitability regarding the following requirements: 1) What type of assessment is used to identify a users type? 2) Can this assessment be applied to children? 3) Can games be categorized based on the model? 4) Can the category be assessed given the model?

2.1 Learning Styles

In a first approach, personalization of the online educational process might be based on how people learn. Learning styles also constitute a mature research area to build on.

The Grasha-Riechmann student leraning scales (Rollins, 2015; Riechmann and Grasha, 1974), Kolb's learning style model (Kolb, 2005), NASSP (Keefe et al., 1986) and Anthony Gregorgc's learning style models (Gregorc and Butler, 1984) have been considered for this purpose.

2.2 Personality Types

A different perspective to personalizing the website is based on the student personality, trying to understand their motivation in order to suggest the appropriate game for the right student.

Myers-Briggs personality type indicator (MBTI) is different from the previous classifications because it defines personality types. MBTI was created based on Jung's typology and is one of the most widely acknowledged and acceptable tests for determining personality types (Myers and Myers, 2010). MBTI uses four bipolar scales to determine the type. These are introversion vs. extraversion, sensing vs. intuition, thinking vs. feeling, and structured vs. unstructured. The four dimensions yield sixteen possible variations, not described in detail due to space constraints.

The MBTI which is a valid and reliable test for classifying people into 16 types and is widely used but can detect types only 50% of the time for children under the age of 12 (MBTI, 2015).

2.3 Gaming Styles

The third approach is based on personalizing the users' experience based on their game preference. Player motivation can provide indicators regarding their personality or learning style.

For this component we choose to look at the Bartle test. The Bartle model was proposed as a model for classifying gamers across so-called Multi-User Dungeons (MUD) (Bartle, 1996). MUDs include games, pastimes, sports, entertainments. It has since been shown to be more generally applicable and correlate with other models for games and has been verified through children questionnaires (Konert et al., 2013). Bartle model thus represents a simple yet representative model that is also well studied in relation to game mechanics and validated in industry, where slight variations of the scheme can be seen in the work by Amy Jo Kim (Kim, 2000), who is well known for her work on Garage Band and SIMs.

The model is convenient to categorize the games through an analysis of game mechanics, such as points, levels and badges, that are used to design games and appeal to players in various ways. The Bartle test is a survey that is valid for older children (Andreasen and Downey, 2008).

The four player types proposed by Bartle are "Achiever" (acting on the world), "Killer" (acting on the players), "Socializer" (interacting with the players) and "Explorer" (interacting with the world).

Table 1: Styles overview comparison (S=Survey, U=undefined, D=defined, NA=not applicable, A=Adults, Se=secondary, All=all ages).

	GRSLSS	KOLB	NASSP	Gregorc	MBTI	Bartle
Assessm. method	S	NA	S	S	S	S
Target group age	A/Se	All	Se	All	>12	All
Games category	U	D	D	U	U	D
Games assessm.	U	D	D	U	U	D

2.4 Overview

Table 1 summarizes the options with information about the four factors we were looking for. Based on the above analysis, GRSLSS, NASSP and MBTI were eliminated because of the targeted group age that does not fit children, starting in first grade. Furthermore, it is not clear how games would be categorized given these models. Kolbs model was eliminated because of the absence of assessment tools. Bartle and Gregorc remain. These models fulfilled the basic factors that are needed for this work. Out of the remaining models, Bartle is the best option because of the system for categorizing games. It is clearer and more informative than Gregorcs because each gamer type has a corresponding favorite game without the need of any further mapping of different models. Finally, creating surveys for children is not straight forward due to language and semantics to get reliable responses. Using Bartle's model through games bypasses that difficulty as will be shown next.

3 METHODOLOGY

The goal is to build a system that collects user feedback in order to personalize the online educational process. Such a system detects user gaming type and suggests games that match in order to enrich and enhance the student experience. This section describes a proposed solution for estimating students' gamer type based on game feedback.

The challenge is to classify both game and user with common variables in order to recommend the appropriate game based on a child's play history. A vector of four variables representing the gamer types (Achiever, Explorer, Killer and Socializer) is chosen to represent a students' characteristics.

3.1 Game Classification

The classification of the game is solved through its game mechanics. A game mechanic is a method that is invoked by agents in order to interact with the game and provides us with the ability to study the systematic structure of a game and analyze how these mechanics help developers create an emotional experience that affects players while using a game. Therefore, a game can be characterized as suitable for a gamer type through the sum of its mechanics. The 22 game mechanics given in Table 2 were used to characterize games. Their descriptions and their affinity with gamer types can be found on Badgeville (Sylvester, 2013).

Table 2: Game Mechanics.

Achievements	Appointments
Behavioral Momentum	Blissful productivity
Combos	Urgent Optimism
Bonuses	Virality
Community Collaboration	Countdown
Discovery	Epic Meaning
Free Lunch	Infinite Gameplay
Levels	Lottery
Ownership	Progression
Quests	Reward Schedule
Status	Cascaded Information

That system is then used to rank the mechanics by their affinity to gamer type. A first approximation is displayed in Table 3. For example, the Achievement mechanic is the goal of the Achievers so it has the greatest effect on this gamer type. Furthermore, Achievements are more important to the Explorers than Killers because Explorers are all about finishing quests aimed at exploring the world while Killers prefer acting on other players. This logic towards ranking them with player types is applied to every element accordingly. (Future work will involve data driven approaches for adjusting these weights.)

Table 3: Effect of Game Mechanics.

Name	Achievers	Explorers	Killers	Socializers	Type
Achievements	4	3	2	0	Progression
Appointments	3	2	0	4	Feedback
Behavioral Momentum	2	4	3	1	Behavioral
Blissful productivity	3	2	1	4	Behavioral
Combos	3	1	4	2	Feedback
Urgent optimism	0	3	4	0	Behavioral
Bonuses	4	1	2	3	Feedback
Community collaboration	2	3	0	4	Behavioral
Virality	2	0	4	3	Behavioral
Countdown	4	2	3	0	Feedback
Discovery	3	4	0	0	Behavioral
Epic meaning	4	3	1	2	Behavioral
Free lunch	1	3	2	4	Behavioral
Infinite gameplay	3	0	4	0	Behavioral
Levels	4	2	3	0	Progression
Lottery	1	3	2	4	Behavioral
Ownership	2	3	1	4	Behavioral
Progression	4	0	3	0	Progression
Quests	3	4	2	0	Feedback
Reward schedules	4	3	2	0	Feedback
Status	2	0	4	3	Behavioral
Cascaded information	1	2	4	3	Feedback

The classification is unbalanced across game type. Equation 1 calculates a balancing factor in order to normalize scores.

$$bfa = \frac{\sum a * bfk}{\sum k}, \tag{1}$$

where bfa is the balancing factor of the achiever class, a is the values in the achiever column, bfk is the balancing factor of the killer class and k is the values of the killer column. All other factors are calculated similarly, resulting in the balancing factors of 0.86 for the Achiever, 1 for the Killer, 1.38 for the Socializer and 0.95 for the Explorer.

When a developer plugs a game into the recommender platform a list of checkboxes appears such as shown in Figure 1, listing all game mechanics along with their definition. The developer checks those game mechanics that apply. The game can then use this information to be characterized in terms of gamer type, given a relationship between a game mechanic and a gamer type according to Table 3.

In an example, assuming the developer has identified the following mechanics: Achievements, Appointments and Blissful Productivity, the resulting vector will add up as shown in Table 4. After normalization with the balancing factor the game profile is obtained. Calculating the percentages results in the game signature, indicating the profile of the gamer type. According to this method, the example game is preferred by Socializers.

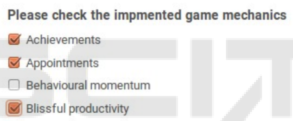

Figure 1: Selecting Game Mechanics.

Table 4: Game Type Detection Example.

	Achievers	Explorers	Killers	Socializers
achievements	4	3	2	0
appointments	3	2	0	4
Blissful productivity	3	2	1	4
Total	10	7	3	8
Game Profile	8.6	6.65	3	11.04
Game Signature	29	23	10	38

3.2 User Classification

User classification is based on the Bartle test for the gamer psychology that classifies users into four gamer types described above. Usually, the type is assessed with a survey, but in the case of children this is difficult because: 1) Survey questions require too much cognitive effort, and 2) Language effects might prevent children from understanding the questions. Studies (Borgers et al., 2000) suggest that upon collecting information from the children the following guidelines should be followed:

1. Avoid Yes and No questions.
2. Avoid writing questions.
3. Avoid suggestions.
4. Keep the questions simple and short.
5. Make it fun.
6. Provide assistance for poor readers.
7. Encourage free recall questions.
8. Use the Visual Analog Scale.(VAS)

Taking these points into account, rather than using a survey, it is preferable to detect a child's gamer type through the history of games played in combination with a feedback. Keeping the question short, fun, easy to understand and using Visual Analogue scales (VAS) as shown in Figure 2. The numbers from -2 to 2 are assigned to the emoticons, with 2, representing "Love it!".

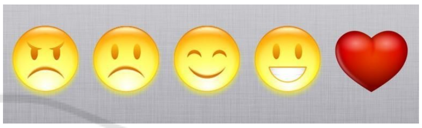

Figure 2: Visual Analog Scale example.

The four variable vector for Achiever, Explorer, Killer and Socializer carry the accumulated feedback output of the user and are used to match the signature of the game. In an example, assume that the user vector is initialized to be equal to 100 and the game vector is as calculated in Table 4. The game signature along with the feedback weighting is then used in order to update the user profile. If the user loved the game the feedback response will be equal to 2. The change rate is therefore the feedback multiplied by game profile and then added to the user profile. This is examplified in a "Love it" scenario in Table 5.

It can be observed given the positive response that the user vector is shifted more or less towards the Socializer games. The next step consists of suggesting new games that match the user signature most closely.

3.3 Training the System

Figure 3 illustrates how the whole system architecture is connected as a simple neural network, given the following variables. **P1** is the contribution of each implemented game mechanic to the game structure F1 is the function responsible of adding the balancing factor.

W2 is the weight or the strength of a bond towards a certain gamer type.

F2 is the function responsible of generating the game and user signatures out of their profiles.

Table 5: Training the system (Scenario 1) in percentage.

	Achievers	Explorers	Killers	Socializers
User profile	100	100	100	100
User signature	25	25	25	25
Game profile	8.6	6.65	3	11.04
Game signature	29.3	22.70	10.24	37.69
Feedback response	2 (=Love it!)			
change rate	17.2	13.3	6	22.08
New User profile	117.2	113.3	106	122.08
New user signature	25.56	24.71	23.11	26.62

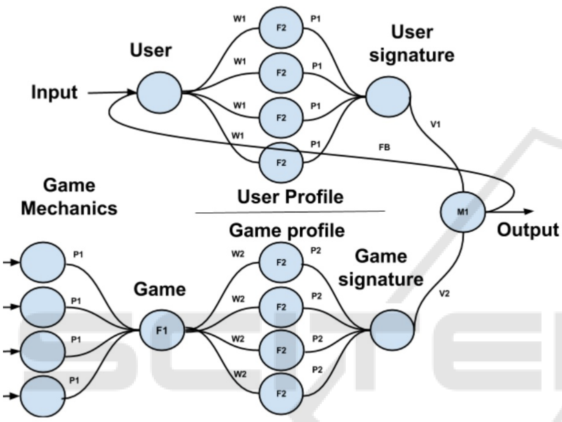

Figure 3: System overview.

P2 are the values responsible for forming a games signature.
V2 is a games signature.
W1 are the values forming the user profile and represents the bond strength to one of the gaming types.
P1 are the values responsible for forming a users signature.
V1 is a users signature.
M1 represents the matching algorithm FB represents the Error function.

4 EVALUATION

The proposed system was evaluated by testing whether a self-categorization using a Bartle gamer type test agrees with the gamer type that is determined through game history and feedback. The feasibility study is performed with adult students as a baseline system, removing one variability factor of submitting elementary school children to the Bartle's test for validation purpose. Future work clearly includes validation with the target group.

4.1 Verification Experiment

The system was tested by asking 61 users to perform the following:

- give feedback on widely popular games by stating their like or dislike of those games
- respond to 10 behavioral questions that collect how the respondent is more likely to do in a certain situation (Bartles Gamer Text) to classify gamer types.

Truth is assumed to be the outcome of the Bartle test in this case. This truth can be compared with the result from the preferences' survey output to study their correspondence. In case of agreement, user feedback would be a valid indicator of gamer type to be used in recommending future games.

For analysis purpose, each respondents provides three basic pieces of information that include their age group, gender and nationality.

The respondents move on to provide their responses to 20 popular games and rate them based on their personal preferences with ”Very bad”, ”Bad”, ”Good”, ”Very good” and ”I dont know the game”. A neutral vote was not provided in order to enforce a decision.

Every choice has its own value (-2. -1, 1, 2 and 0 for the choices ”Very bad”, ”Bad”, ”Good”, ”Very good” and ”I dont know the game” respectively) that are then multiplied with the game vector. The values assigned to the game are based on our knowledge of each game's game-mechanics and are listed in Table 6, with 4 being the best fit and highest possible number. Their detailed calculation is omitted for space reasons. The table shows the games in the order of presentation in the survey.

For every question the response value is multiplied by the game's vector resulting in the output that is to be used to detect the gamer type as illustrated in an example below in Table 7.

The sum of the new values after being modified by the response values for each gamer type is calculated independently and then multiplied by the balancing weights. The above mentioned 4 games are used in an example given in Table 8. Based on these 4 games and the 4 responses the user tends to be an Explorer and his secondary type is Achiever.

The next step is getting the output out of the behavioral multiple choices questions, 10 of which are included in the survey to be ranked by the respondents.

An example score development is depicted in Table 9, showing that this user is an Explorer and that his secondary type is an achiever.

Table 6: Distributed weights of games.

Game Name	Achievers	Explorers	Killers	Socializers
Farmville	3	2	1	4
Call of Duty	2	1	4	3
Chess	1	4	3	2
Angry birds	4	1	3	2
Pirate Kings	2	1	3	4
Guitar hero	3	1	4	2
Assasins' creed	3	4	2	1
Super Mario	4	3	2	1
Trivia crack	2	1	3	4
Counter Strike	2	1	4	3
GTA	2	4	3	1
Candy crush	4	1	2	3
Zuma	2	1	3	4
2048	3	1	4	2
The Sims	2	4	1	3
Fruit Ninja	4	1	3	2
Clash of clans	1	3	2	4
Need for speed	3	2	4	1
Monopoly	1	4	2	3
Crazy taxi	4	3	2	1

Table 7: User type detection.

Game Name	Achievers	Explorers	Killers	Socializers	RATING	New Achievers	New Explorers	New Killers	New Socializers
Chess	1	4	3	2	2	2	8	6	4
Angry birds	4	1	3	2	1	4	1	3	2
Pirate Kings	2	1	3	4	-2	-4	-2	-6	-8
Guitar hero	3	1	4	2	-1	-3	-1	-4	-2

The last step is to compare the output from both methods in order to determine whether they match. Three methods for judging the results are employed.

1. Successful match: This means that the 2 methods concluded that the respondent belongs to a certain gamer type.
2. Close match: Which was included because some analysis of responses were not entirely wrong so some conditions to detect close results and they are:-
   (a) 5% deviation in the behavioral test.
   (b) 5 points deviation in the preferences' assessment.
   (c) First type came second.
   (d) Second type came first.

Table 8: Adjusting User profile based on game reviews.

	Achievers	Explorers	Killers	Socializers
Initial State	100	100	100	100
Responses summation	-1	6	-1	-4
Updated state	99	106.0	99.0	96
Balancing weights	1	1.42	0.76	1
Final State	99	150.92	75.24	96

Table 9: User type detection.

	Achievers	Explorers	Killers	Socializers
First question	3	4	2	1
Second question	2	4	3	1
Third question	2	4	3	1
Fourth question	4	3	2	1
Fifth question	4	3	2	1
Sixth question	3	4	2	1
Seventh question	1	4	3	2
Eighth question	1	3	2	4
Ninth question	2	4	3	1
Tenth question	3	4	2	1
Total	25	37	24	14

3. Mismatch: All other responses that do not follow any of the above mentioned rules.

In the examples that we used for illustration the results came out like this:
The output of game rating: Achiever:99.0; Explorer:150.92; Killer:75.24; Socializer:96.0
The output of Bartle's test is: Achiever:25; Explorer:37; Killer:24; Socializer:14
Both methods result in Explorer, indicating a successful match.

4.2 Compiled Results

The Questionnaire was released to a larger number of people and 63 responses were collected; 2 of them were invalid, resulting in a total of 61 responses. Their distribution is given below.

- 11 different nationalities which are Egyptian, German, Dutch, French, Russian, Indian, Mexican, Indonesian, Colombian, American and Syrian.
- Gender: 34 males (55.78 %) and 27 females (44.22 %).
- Age groups(Years old): 15 -17 (1.7 %), 18 - 21 (34.9 %), 22 - 24 (56.9 %), 25 - 28 (4.8 %) and Older than 28 (1.7 %).

The Questionnaire results came out to be:-

- 33 Successful matches (54.10 %).
- 16 Close matches (26.23 %).
- 12 mismatches (19.67 %).

Table 10 depicts the confusion Matrix for the results.

Table 10: Results overview.

Games' feedback \ Behavioral Questionnaire	Achievers	Explorers	Killers	Socializers	Total
Achiever	4	6	1	0	11
Explorer	3	21	8	3	35
Killer	2	5	8	0	15
Socializer	0	0	0	0	0
Total	9	32	17	3	61

It is interesting to observer a non-uniform distribution among player types. There are more Explorers and few Socializers. One could imagine that the questionnaire is biased. However, this result seems to be common. As an example, middle and high school teacher Douglas Kiang posted on Edudemic his experience when he made one of his classes take the Bartle's test for gamer types in order to have a better understanding of his students and also to be able to form collaborative groups (Kiang, 2007). His class had 5 Achievers (21.74%), 9 Explorers (39.13%), 6 Killers (26.08%) and 3 Socializers (13.04%), a similar distribution to the one observed in our study.

4.3 Questionnaire Redesign

Trying to enhance the success rates, some of the questions that we considered insignificant were removed because some games managed to carry almost the same feedback for all users. One of those games is Super Mario as shown in Figure 4, which 92% of the respondents rated as good or very good respectively.

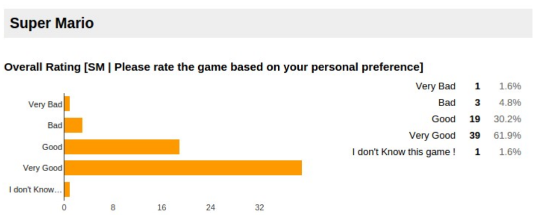

Figure 4: Game question analysis.

Two additional games, chess and monopoli, serve little as discriminator between gamer types. Respondents thought that they are good and very good with the rates of 92.2% and 89.1% respectively. The games were dropped from the questionnaire.

The data was reprocessed with the remaining 17 game rating questions. After recompiling responses using the modified questionnaire the results are given in Table 11.

1. From 33 successful matches (54.10 %) to 40 (65.57%) with an improvement of 7 matches (11.47%).
2. From 16 close matches(26.23 %) to 13 (21.31%) with an improvement of 3 matches (4.92%).
3. From 12 mismatches (19.67 %) to 8 (13.11%) with an improvement of 4 matches (6.56%).

Table 11: Results overview.

Games' feedback \ Behavioral Questionnaire	Achievers	Explorers	Killers	Socializers	Total
Achiever	5	6	1	0	12
Explorer	1	21	2	1	25
Killer	3	5	14	2	24
Socializer	0	0	0	0	0
Total	9	32	17	3	61

5 CRITICAL REFLECTION AND FUTURE WORK

This paper addresses the need for a motivating learning platform for children without access to teachers through the use of games. We explore a recommender system based on factors that allow us to match users with games using Bartle's gamer types as a first approximation.

Bartle's test, though usable with children and adults, has fundamental critiques as to its usefulness in the literature, reasoning that it is a theoretical model. While the model may not be sufficient as the types overlap and are not defined with enough detail (evident in the way Table 3 had to be constructed) the model is nonetheless a good starting point according to Yee (Yee, 2006b). Yee breaking the types down into motivation factors that make up various types. His work is founded on very large data sets. Our approach is somewhat similar. We use Bartle's types as a guideline for understanding the game mechanics. These are the factors that we use to relate players to games. Game mechanics are consciously used by game designers when creating their games. They are therefore easy to use as descriptions of the game. The game mechanics constitute factors in a similar way as the motivators in Yee's work and can be used in turn in order to reconstruct gamer types. Bartle's basic definition thus provides a boot-strapping method for retraining a feature network using a knowledge-base design. Weights can later be retrained using data driven approaches.

Future work involves a larger collection of data from the target audience that would allow data driven parameter training in order to match game mechanics to data driven user types.

The resulting recommender system can supplement other such systems that have been well researched in the literature.

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