Toward a Propensity-Oriented Player Typology in Educational Mobile Games

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ABSTRACT
The pivotal role of identifying types of players is inevitable in the game contexts, and educational games are not an exception. This study aims to present a model of player-game interaction in the mobile game-based learning setting regarding the behavioral propensity. This model comprises five different features inherited from the player typology literature including precision, perfection, punctuality, presence, and pace. To this end, we analyzed the activities of players in a mobile educational game and then tried to classify players based on their preferences in how to deal with the game. Furthermore, as a step toward determining the association of features with each other, multiple linear regression analysis was conducted. The outcome of above investigations resulted in a model representing player interaction with the game in a way that it could be used to classify different types of players in educational mobile games.

Keywrods: Player Typology, Game-based Learning, Gamification, Mobile Learning, Player Engagement

INTRODUCTION
Computer games have been designed to promote learning process of individuals in ways that attract them, bringing about a continued interest in the game for a substantial amount of time and keep them involved in the game environment. The design of educational games could have three purposes, they may be designed to promote learning or to develop cognitive skills, or to take the form of simulation allowing learners to practice their skill in a virtual environment (Deterding et al. 2011). In the field of game-based learning and particularly mobile educational games, studies proved that gamified curricula will become more and more popular as a method to induce engagement in students (Crisp 2014).

Recent developments in game business have especially elevated the need for distinguishing between types of players and play styles (Hamari et al. 2014) and educational mobile games as a recently appeared branch of the games is not an exception. As using games for educational purposes has been gained a notable respects among researchers, since it has potentials to promote player-game interaction for education purposes, the need for gaining a broad knowledge of the players and their characters is becoming more essential. Sabourin and Lester (2014) in their study stated that a game-based learning environment has the ability to both uphold learning and boost engagement of players. Therefore, considering types of players and their playing styles in the design of the educational mobile games is a necessary step toward improving personalization and customization of the games to make players more engaged and fulfilled.

Despite various research which has been conducted to study player typology in the digital games, lack of a model or framework distinguishing different player types in the game-based learning environments
and particularly educational mobile games is perceptible. Initially, this study aims to define and present a model representing player-game interaction in the setting of educational mobile games regarding the behavioral propensity of players in dealing with the game. Furthermore, it considers how players could be classified into different groups showing different tendencies toward using an educational game and how the defined features are correlated to each other. This would enable us to gain a perspective about player types and a profound understanding of players' behavior in the game. This research, in fact, is the next step of our posterior work on player engagement in educational mobile games (Gholizadeh et al. 2017).

The following section presents the theoretical background about player typology literature. Next, the proposed model presented along with a description of each feature in it. The methodology of the study including research design, context, and data collection process will be expressed. A multiple linear regression analysis and results follow. Section five discusses the practical and theoretical contributions regarding the results. The conclusion section reviews the most important findings and expresses the limitations and future directions of the study.

LITERATURE REVIEW

Digital Game-Based Learning

Digital game-based learning is the product of a balance between learning and gaming elements. In the other words, entertaining intrinsic of games has potentials to be coupled with the learning process and improve it. Therefore, two important elements of educational games are entertainment and educational component separating educational games from entertaining games and e-learning applications (Bellotti et al. 2013). Two types of games can be distinguished in educational games: special purpose games which have been developed to promote educational purposes and Commercial-Off-The-Shelf games that have been developed with entertainment objectives, but that are being used in an educational context. Note, however, that this does not mean that special-purpose DGBL games cannot be commercially available (Stewart 2013).

The design of educational games could have three purposes, they may be designed to promote learning or to develop cognitive skills, or to take the form of simulation allowing learners to practice their skill in a virtual environment (Erhel & Jamet, 2013). Games that are developed with the primary goal of achieving knowledge transfer are typically used in education, in order to teach math (Castellar et al. 2015) or language (Palomo-Duarte et al. 2017), for instance.

Player Engagement

Engagement is a quality of user experiences with technology that is signified by challenge, aesthetic and sensory appeal, feedback, novelty, interactivity, perceived control and time, awareness, motivation, interest, and affect (O'Brien & Toms, 2008). In the process of learning for youth and adults who are using an instructional technology such as an educational game, engagement drives moment-by-moment use, as well as the learning that occurs during play and preferably transfers afterwards. Learners who are engaged in educational activities show involvement through their behaviour (Deater-Deckard, Chang & Evans, 2013).

A usual incentive for using digital games to support learning is a belief that games can operate as useful primers for active and more profound learning engagement with subject matter, by providing an engaging and contextualized setting for authentic problem solving (Gee 2009). Although there is an increasing number of studies carried out to survey or synthesize the experimental evidences of gaming for learning (Connolly et al. 2012; Girard, Ecalle & Magnan, 2013), in terms of player engagement features,
the literature still lacks a comprehensive conceptualization. Moreover, there is a need for examining how the game-based learning engagement emerges and develops during gameplay (Ke, Xie & Xie, 2015).

**Player Types**

In literature, the four main categories of segmentation including geographic, demographic, psychographic, and behavioral have acquired an established standing. Behavioral segmentation is concerned with how players, users or customers behave with and within products and service (Hamari & Tuunanen, 2014). In gamified educational context, the goal of segmentation is to serve learners in a more bright way by being able to offer products that better match their needs and tendencies.

The studies on player typologies and categorization seem to have focused mainly on behavioral aspects. Ip and Jacobs (2005) studied player typology and divided user population into hardcore and casual players. As opposed to casual players, hardcore players are people who are more dedicated to gaming in almost every way, demonstrating, for example, playing longer sessions more often and spending time discussing on game-related forums (Hamari & Tuunanen, 2014). Bartle (1996) is one of the most referenced authors regarding player typology. Based on the Bartle’s player types, playing has two dimensions, i.e. action vs. interaction and player-orientation vs. world-orientation in which four types of player is defined. First of the types is Achiever who prefers action to act upon the world and environment. An Explorer favors interaction and is also world-oriented. Killers prefer action, but fronting the Achievers, they do the same on players. Socializer, the last type, prefers interaction with other players.

Drachen et al. (2009) identified four different styles each with different playing patterns and solutions to specific problems and also a certain level of performance. By using game log information the players were divided into the four groups including Veterans, Solvers, Pacifist, and Runners. Veterans, as the name suggests, are the most experienced players. Solvers take their time to solve the puzzles faced during the play. Pacifists die mostly from enemies and are fairly fast at completing the game. Runners are named according to their swift play-through of the game.

**METHODOLOGY**

**Research Question**

Player typology is a well-studied subject in the contexts of different genres of games. However, the educational nature of games has not been considered adequately so far. This may be problematic with respect to the generalizability of prior works, as the benefits of using games for educational purposes has become more of a focus. It is interesting to propose the question of how players in mobile educational games could be categorized, taking account behavioral propensity of players. Hence, this paper attempts to explore the potential answers and take a step towards presenting a player typology in digital game-based learning practices.

**Research Design**

The initial aim of this study is to present a model of player-game interaction in educational mobile games comprising behavioral features inherited from player typology’s literature in game practices. Since using game features in non-games contexts or for purposes beyond entertainment has potentials, it would be useful to see the users of educational games as players and try to classify them like how players in games are classified, which is known as player typology.

There four main categories of segmentation in literature including geographic, demographic, psychographic, and behavioral. In geographic segmentation, people are divided into groups based on their place of residence. For example, country, province, city or so on. In demographic segmentation,
individuals are categorized according to many descriptive features, such as age, gender, education, occupation or social status. Psychographic segmentation is a more sophisticated approach since it tries to group people according to their attitudes, interests, values, and lifestyles. An example could be a social extrovert who enjoys meeting new people and share new ideas with others. Lastly, there is behavioral segmentation which is an approach that tries to find patterns in consumers’ behavior towards or with a product. In this study, we particularly use behavioral viewpoint to categorize people.

In this study, all features in player typology literature are considered in the first step. Furthermore, the generalizability of this model is also respected so that it could be used for a wide range of educational games. In the selection phase, five features were chosen including Precision, Punctuality, Perfection, Pace, and Presence that are aligned with the nature of mobile games for educational purposes explaining how player tend to behave toward an educational game in mobile devices.

After presenting the model, the association of each feature to other features will be determined using statistical methods. The inferential statistical analysis explains the role of each feature in others' changes and explains how one describes each other variability by exploring the correlation between them. The research data is related to an educational mobile game aiming to learn English vocabulary. In this game, the mechanisms for measuring these five features are built purposefully to facilitate the process of gathering data from the players.

**Collecting Users’ Data**

To do statistical tests and find the relationships within the quintuple model, a mobile educational game aimed at learning of English vocabulary was developed and has become available to the public through Google Play. The aim of this game is that routine words in English are trained in the form of fascinating challenges to the players. Mechanisms built into the game, will facilitate learning, and remembering the words for players. In the game, 500 words are included which are divided to 30 different lessons from the various categories. These categories include food, tools, clothing, and all thing which people experience in everyday life. Each lesson, on average, has about 15 words in it. Each lesson builds based on common and frequently-used word. For example, in fruits category, only the name of those fruits will be included which are common among world people and do not belong only to a specific geographical location. Figure 1 presents the main scene of the game on a mobile device.

![Figure 1. Main scenes of the game on a mobile device](image)
With an initial analysis of the data collected to a specific version of the game, the extent of each feature for every player is stored in a dataset. After then, the cleaning operation was conducted through which the erroneous data or records that are related to inactive players removed. In the initial dataset, there was information pertaining to about 876 players who had used this particular version of the game and their information was sent to the game server. After the cleaning operations of inactive or less active players, the population of the dataset under evaluation reached to 575 users. Since there is no limited or controlled sample of users, it was expected that the demographic factors would be diverse. In other words, it is not restrained to a certain category of users. However, the only demographic data collected from the users were their age and gender.

THE QUINTUPLE MODEL

Players tend to deal with the game in a wide range of propensities. In this quintuple model, every feature stands for a specific motivation of the player engaged in the game. Through this model, players could be classified based on their state in every distinguishing feature. In other words, each feature perceives the player-game interaction by different views.

The given name of the model is five pieces of player engagement comprising Punctuality, Presence, Perfection, Precision, and Pace. The chosen features have resembled from the aspects of player types applicable to single-player educational games implemented on the mobile platforms.

Presence
This feature is a time-related feature resembled time aspect of hardcore players in the Ip and Jacob’s study indicating how such players tend to play longer sessions more often (Ip & Jacob, 2005). The presence feature indicates how long a player spends in the game or application environment. Players with high presence rate are the ones who tend to stay in the game environment long enough to find intact areas of the game, connect with other players, collect virtual items, check out their statistics and learn a wide range of knowledge presented by the game.

Punctuality
This feature has the same focus on time as Presence, but concerning the discipline and regularity of the player's presence in the game. Punctual players prefer to run the game frequently on a daily basis. Persistency is the main characteristic of such players so that they could keep track of game changes and follow up their status.

Precision
This feature is a representation of the main trait of the solver players in the Drachen’s study taking their time to solve the puzzles encountered during the play patiently. Error-free players try to be neat and take their steps carefully in the challenges. The quality of player attention toward the games is pivotal here so that they would be mentally alert.

Pace
This feature is also retrieved from the Drachen's study regarding runner players having a swift play-through of the game (Drachen et al. 2009). Swift players like to have the final badge or trophy in their hand in the shortest time. They hold the idea that spending too much time in every single stage of the games is a waste of time and is better to take a pace toward the end of story.
Perfection
This feature comes from Achiever players in Bartle's player types whose main feature is to achieve the objects located in the game environment in a perfect manner (Bartle 1996). Some of the players are perfectionists who drive themselves to excel. These players are ambitious with high standards.

Player Profile
Each user playing the game has a player profile comprising features of the quintuple model in which every feature is measured. In Figure 2, a user profile based on the quintuple model is depicted. As an example, Shahram has a swift progress through the levels, stay in the game for fairly long sessions, get scores in each stage in a moderate way, and prefers to show less correctness and regularity.

RESULTS
To analyze and get a profound knowledge of the nature of the model, we need to analyze the interrelationships among all features. Firstly, for each feature, a parsimonious model should be determined to contain the best subset of other variables from the model. Secondly, the obtained parsimonious model would be used to conduct multiple regression analysis. This analysis will give us knowledge about how each feature is associated and correlated with other features and how each feature can explain the variability of the features.

Stepwise Model Selection
Parsimonious models are simple models with great explanatory predictive power. They explain data with a minimum number of parameters, or predictor variables. There is generally a tradeoff between goodness of fit and parsimony: low parsimony models (i.e. models with many parameters) tend to have a better fit than high parsimony models. This is not usually a good thing; adding more parameters usually results in a good model fit for the data at hand, but that same model will likely be useless for predicting other data sets. Finding the right balance between parsimony and goodness is the goal here.
For each feature, the parsimonious model was obtained using backward elimination considering adjusted R-squared criterion. R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determination for multiple regression. For instance, 100% indicates that the model explains all the variability of the response data around its mean. The adjusted R-squared is a modified version of R-squared that has been adjusted for the number of predictors in the model. The adjusted R-squared increases only if the new term improves the model more than would be expected by chance. It decreases when a predictor improves the model by less than expected by chance.

In this method, multiple linear models with all the features in the first phase are done and the adjusted R-squared result is recorded. Then in the second phase, different models created by the removal of one of the features and the value of adjusted R-squared criterion was obtained for each one. If in a new step, the value of adjusted R2 were enhanced, the model with the highest adjusted R2 would be selected to continue the task and then the different sub-models from the selected model would be tested. This cycle continues until the resultant sub-models in each phase would not cause the increase in adjusted R2. Table 1 summarizes the stepwise model selection for all of the presented features and final parsimonious models.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Obtained model</th>
<th>Adjusted R²</th>
<th>Removed variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision</td>
<td>Pace + Presence + Punctuality + Perfection</td>
<td>0.191</td>
<td>-</td>
</tr>
<tr>
<td>Perfection</td>
<td>Pace + Presence + Precision</td>
<td>0.395</td>
<td>Punctuality</td>
</tr>
<tr>
<td>Punctuality</td>
<td>Pace + Presence + Precision</td>
<td>0.148</td>
<td>Pace</td>
</tr>
<tr>
<td>Presence</td>
<td>Precision + Punctuality + Perfection</td>
<td>0.319</td>
<td>Pace</td>
</tr>
<tr>
<td>Pace</td>
<td>Precision + Punctuality + Perfection</td>
<td>0.116</td>
<td>Presence</td>
</tr>
</tbody>
</table>

*Table 1. Obtained parsimonious models for each feature using stepwise model selection*

After obtaining the parsimonious model of each feature, multiple linear regression analysis was performed for each feature, which is expressed individually in the following sections.

**Multiple Linear Regression Analysis**

Multiple regression is an extension of simple linear regression. It is used when we want to predict the value of a variable based on the value of two or more other variables. It attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. At the center of the multiple linear regression analysis is the task of fitting a single line through a scatter plot. More specifically the multiple linear regression fits a line through a multi-dimensional space of data points. The simplest form has one dependent and two independent variables.

There are 3 major uses for multiple linear regression analysis. First, it might be used to identify the strength of the effect that the independent variables have on a dependent variable. Second, it can be used to forecast effects or impacts of changes. That is, multiple linear regression analysis helps us to understand how much will the dependent variable change when we change the independent variables. Third, multiple linear regression analysis predicts trends and future values. The multiple linear regression analysis can be used to get point estimates.
Results for the regression analysis of the Precision variable is provided in Table 2. Among the explanatory variables, the perfection variable was significantly correlated and other variables with the p-value of higher than 0.05 were not significantly correlated.

|              | Estimate | Std. error | T value | Pr>|t| | Significance |
|--------------|----------|------------|---------|----------|----------------|
| (Intercept)  | 7.042e-02 | 4.254e-02  | 1.655   | 0.0984   |                |
| Pace         | -1.503e-02 | 3.781e-03  | -3.976  | 7.91e-05 | ***            |
| Presence     | 7.465e-06  | 5.811e-07  | 12.846  | <2e-16   | ***            |
| Precision    | 5.236e-01  | 5.921e-02  | 8.844   | <2e-16   | ***            |

*Table 2. Results of Multiple regression analysis for the Perfection response variable*

Table 3 presents the tests for the Perfection feature. All explanatory variables have achieved a significant p-value. In addition, the value of adjusted R-squared is 0.39, making this model adequate enough to predict the response variable which is the Perfection feature.

|              | Estimate | Std. error | T value | Pr>|t| | Significance |
|--------------|----------|------------|---------|----------|----------------|
| (Intercept)  | 7.042e-02 | 4.254e-02  | 1.655   | 0.0984   |                |
| Pace         | -1.503e-02 | 3.781e-03  | -3.976  | 7.91e-05 | ***            |
| Presence     | 7.465e-06  | 5.811e-07  | 12.846  | <2e-16   | ***            |
| Precision    | 5.236e-01  | 5.921e-02  | 8.844   | <2e-16   | ***            |

*Table 3. Results of Multiple regression analysis for the Perfection response variable*

Multiple linear regression results for the Punctuality variable is provided in Table 4. All three explanatory variables have achieved a significant p-value. The value of adjusted R-squared is 0.31, which means that the model at least can explain the 31 percent of the variability of the punctuality variable.

|              | Estimate | Std. error | T value | Pr>|t| | Significance |
|--------------|----------|------------|---------|----------|----------------|
| (Intercept)  | 6.583e-01 | 5.180e-02  | 12.710  | <2e-16   | ***            |
| Pace         | 3.218e-02  | 4.603e-03  | 6.992   | 7.59e-12 | ***            |
| Presence     | -3.634e-06 | 7.075e-07  | -5.136  | 3.85e-07 | ***            |
| Precision    | -1.349e-01 | 7.208e-02  | -1.872  | 0.0617   |                |

*Table 4. Results of Multiple regression analysis for the Punctuality response variable*

Multiple linear regression results for the Presence variable is provided in Table 5. Among the explanatory variables, Punctuality and Perfection have been set significant in the test. The value of adjusted R-squared is 0.31.
|                | Estimate | Std. error | T value | Pr(>|t|) | Significance |
|----------------|----------|------------|---------|----------|--------------|
| (Intercept)    | -1931    | 3020       | -0.639  | 0.523    |              |
| Precision      | 5312     | 3943       | 1.347   | 0.178    |              |
| Punctuality    | -8685    | 2037       | -4.264  | 2.35e-05 | ***          |
| Perfection     | 28759    | 2292       | 12.546  | < 2e-16  | ***          |

Table 5. Results of Multiple regression analysis for the Presence response variable

Lastly, the results for the Pace variable is provided in Table 6. Punctuality and perfection have been set significant variables. The value of adjusted R-squared is 0.11.

|                | Estimate | Std. error | T value | Pr(>|t|) | Significance |
|----------------|----------|------------|---------|----------|--------------|
| (Intercept)    | 0.2308   | 0.5076     | 0.455   | 0.649    |              |
| Precision      | 0.7673   | 0.6627     | 1.158   | 0.247    |              |
| Punctuality    | 2.3466   | 0.3423     | 6.855   | 1.86e-11 | ***          |
| Perfection     | -1.5425  | 0.3853     | -4.004  | 7.06e-05 | ***          |

Table 6. Results of Multiple regression analysis for the Pace response variable

**DISCUSSION**

In Figure 3, the ultimate model of interrelationships between features is illustrated. Findings showed that variability of a feature can be predicted from other features’ changes and the interrelationships in the present model are statistically significant. As it can be seen, the analysis of the statistical tests resulted in this model containing significant correlations among features of player-game interaction.

Correlation is a form of dependency, where a shift in one variable means a change is likely in the other, or that certain known variables produce specific results. A positive correlation does not guarantee growth or benefit. Instead, it is used to denote any two or more variables that move in the same direction together, so when one increases, so does the other. Negative correlation is used in statistics to measure the amount that a change in one variable can affect an opposite change in another variable. There are three positive correlation and three negative ones. There is no isolated node in this model implying that the feature selection phase had been well conducted so that not only each feature is independent but also the selected features have enough bonds to each other.
Positive Correlations

The Punctuality and Pace features are positively correlated. Punctual players, who play the game frequently in a daily basis, are expected to pass the challenges in the game due to the fact that their regular presence can lead them to take many steps towards the end to the levels. On the other hand, if you want to reach the final point, you should use the game more frequently.

The results show a positive correlation between Perfection and the Precision features. This finding gives us the viewpoint that alert players tend to be a perfectionist in winning scores. Furthermore, it shows that perfectionist players make fewer errors in playing due to their experience and virtue of seeking the underlying goodness.

Another positive correlation is between Presence and Precision features. As players stay longer in the game environment, they will achieve intense and precise knowledge of the details, leading to a fewer number of mistakes in playing. The practical experience of being usually present in the game plays a significant role in terms of becoming a master player.

Negative Correlations

There is a negative correlation between Perfection and Pace features in our findings. This finding particularly could be speculated beforehand, as it is undeniable that perfect steps ought to be gently taken. Players should stay longer at a level if they are willing to get more score and complete perfection-related badges. On the other hand, the desire to set in the final stage makes players to take their steps as quickly as possible and move swiftly through the level up to the final stage.

The correlation between Pace and Precision features are confirmed to be negative. It seems that being a swift player make you show less precision and perfection in your in-game activities. In other words, Taking care of every detail in your play style make your moves heavy and slow. It is almost unlikely to reach the final stage in a short time and have every badge and score on your way.

In the selection phase, these two features considered as time-related features. In the results, it was revealed that there is a negative correlation between them. This finding indicates that there is two different attitude toward being present in a game. First, players who stay longer in the game don’t need to
run the game in a near future because they might become satisfied enough to leave the game for a while. In a comparable way, staying too long in a game would be nonsense, if a player is likely to be back soon.

**Application of the resulted model**

Linear regression analysis helps us to predict the value of $Y$ for a given value of $X$ or vice versa. In this model, the resulted relationships can be used to predict a part of the model, which is considered as the primary application of it. In some settings, it would be impracticable or costly to measure some of the features of player-game interaction due to different causes including the nature of the game, lack of the tools, reliability issues, the player’s situation, and etc. Therefore, using a related available feature to predict an unknown feature is one of the best options in such situations. In addition, by having the knowledge of correlated relationships, supervised changes in one feature can influence on one other feature. Such changes can be imposed on players through establishing clear goals, designing an immersive scenario, using game’s elements and mechanics, and so on. As an example regarding this model, if the scenario of the game is designed in such a way that the player's progress is based on his regular presence, it could be expected that the pace of the player progress is raised consequently. It is especially respected useful in conditions that the designer of the educational game does not have the feasibility to directly influence player's pace, but the capability to use the existing functionality in the game to improve players' punctuality.

The most important value of this model categorizing players in terms of their behavioral propensity is using this model to personalize an educational game. By being aware of players' tendencies towards the game, either directly or through prediction, give us the ability to provide an educational game to users that accommodate the users' need and character. Based on our finding, players can be categorized based on their priority in being good at each feature in the model. For instance, some players may like to be wide-awake while playing, creating complex challenges are welcomed by such players. Watchful players have potential to face complex challenges with surprising parts and hopefully overcome. In contrast, for players with less accuracy, proper guidance and simplification would be helpful as they don't like always jumping over hurdles. Perfectionist players hold great hopes to obtain high scores and stand on the highest stages. Since they have the inclination to acquire ambitious goals, set great clear goals for them would be a way to engage them in the game. Players who are not so perfectionist can be directed by practical goals.

Players with a daily presence in the game are the ones who are aware of any changes in the game and are up-to-date users. Frequent players are on the edge of being bored by repetition and routine. However, such players are interested in having various contents in the game. Moreover, mechanism of reviewing the lessons in educational games work well on these players. Speaking of the length of players' presence in the game, this long presence can be seen as an opportunity to take advantage of it. Some specific challenges require players to stay long enough to acquire the knowledge or skill. Finally, players with swift progress and pace in the game are able to overcome short-term challenges and tend to steps quickly without being aware of details.

**CONCLUSION**

To sum up, this study was directed to present a quintuple model of player-game interaction to categorize players in educational mobile games based on their behavioral propensity. To this end, the interrelationship among features in the form of correlations has been discovered using multiple linear regression analysis. Subsequently, the interrelationships within the model were interpreted in terms of personalization and customization in the contexts of educational game practices. The findings of the study
help researchers and game designers profoundly understand the nature of players' tendencies and motivations in this contexts. On the whole, this model is applicable to other types of educational games and even non-educational ones. Coupled with the literature and prior studies, it seems reasonable to assume that this study starts a way toward developing a player typology for educational mobile games. Though, it is worth noting that there are still sparse dark and intact areas in this field that need to be dealt with.

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