Engagement-Based Player Typologies Describe Game-Based Learning Outcomes

Stefan Slater[1], Ryan Baker[1], Valerie Shute[2], and Alex Bowers[3]

[1] University of Pennsylvania, Philadelphia PA 19104, USA
[2] Florida State University, Tallahassee FL 32306, USA
[3] Teachers College Columbia University, New York City NY 10027, USA

Abstract. Engagement is a strong predictor of learning in educational contexts, but the definition of engagement can vary from study to study, with small differences in definition leading to substantial differences in findings. In addition, students frequently employ strategies in online learning systems that the system designers may not have expected, which can challenge the assumptions made in these definitions. Students playing educational games employ a particularly wide variety of strategies and behaviors, which can make measuring overall engagement with the game challenging. In this study we examine student engagement by describing players' profiles of behaviors and interactions with a physics-based simulation game, Physics Playground. To identify possible subgroups of players we use Latent Profile Analysis (LPA), a type of person-centered mixture model that assigns individuals to a set of mutually exclusive classes based on patterns of variance in a set of response data. We found support for two classes of players – high engagement players and low engagement players – and we show that students' membership in these classes is predictive of their performance on a posttest assessment. We end by discussing the limitations of this method, as well as the potential for identification and analysis of these types of player profiles to be used in adaptive game mechanics and personalization of learning contexts.

Keywords: Game-Based Learning, Mixture Modeling, Engagement Profile, Player Typology.

1 Introduction

The designer of an AIED system typically has an implicit context in which they expect the system will be used. However, individuals playing games -- educational or not -- generally seem to manifest a range of gameplay strategies and styles that can be difficult for a system designer to account for. There has been considerable research on the different ways that people orient themselves to non-educational games (Bartle, 1996; Williams, Yee & Caplan, 2008), suggesting that players have a wide range of motivations for play. Some players report that they enjoy social interaction, others immersion in a detailed world, and others in-game measures of their achievement. What a player says they enjoy doing in a game, and what they do when playing that game, however, can be very different. For a deeper understanding of the different approaches that players use to engage with games, it's crucial that actual play data be used in conjunction with students' evaluations of enjoyment and motivation in play. Some research efforts have attempted to do this, as well as determine if these typologies are also seen in educational games. Slater et al. (2017) attempted to replicate Bartle's original typologies in a physics simulation game, identifying achiever and explorer classes of players, using log data collected from within the game environment during play. A third group was also identified, called disengaged players. They hypothesized that this latter group might have consisted of students who, in other games, might be socializers and/or killers, as the game studied was a nonviolent, single-player game, and there were no multiplayer elements for these types of players to partake in.

In this work, we replicate and extend Slater et al.'s study, using a later data set from the same physics simulation game. We construct a typology of game players from multiple variables created by logged game actions recorded by the system. We then use latent profile analysis to construct a typology of players in the game and measure performance differences between groups of players on a post-test assessment. By connecting learning to these typologies, we can understand how styles of play relate to learning gains in digital games.

2 Methods

We conduct this research using *Physics Playground*, an educational physics simulation game developed by Valerie Shute's lab at Florida State University (Shute, Almond, & Rahimi, 2019). In Physics Playground, students draw simple machines to navigate a ball through obstacles and to a balloon somewhere else in the level. The game contains worked examples and hint-based physics lessons to help students that are having difficulty solving levels. Data were collected from 199 high school students in the southeast United States as part of a broader study on Physics Playground (for study details see Shute et al., 2021). The study took place over six days, and students spent approximately 250 minutes on gameplay. Student actions (e.g. menu navigation, level start, stop, and completion, objects drawn, and hints used) were recorded by the system.

Following data collection, gameplay features were constructed from the log data generated by the game. Our final feature set consisted of 8 features, covering multiple different facets of game interaction: number of gold and silver coins earned for level completion; number of unique levels and total levels visited by the player; number of machines, number of total drawings, and number of erases made by the player; and number of times the player used the learning support button. Each feature is summed across a student's entire record of play. Using a limited feature space was necessary due to the use of Latent Profile Analysis (LPA) as our modeling approach (Jung & Wickrama, 2008) in the statistical software program MPlus (Muthen & Muthen, 2017). In developing our features we ensured that multiple different elements of gameplay were represented, both in terms of level-to-level behaviors as well as within-level behaviors, so that our resulting groups of players would be representative of a multivariate measure of engagement in Physics Playground. We also included one distal learning outcome, consisting of students' score on an 18-item post-test that measured students' physics knowledge.

3 Results

We found statistical support for the existence of two distinct classes of Physics Playground players in our data. This model consists of two groups: (a) low engagement (Class 1, red, $n = 146$), with below-average mean scores on all measured variables, and (b) high engagement (Class 2, blue, $n = 53$), with above-average mean scores on all measured variables. Players in the two classes differed significantly for all features except for the number of gold coins earned and the number of learning supports used. In each case, the blue high engagement group had higher mean scores than the red low engagement group. This difference in engagement was apparent both in terms of overall progression, in the case of unique levels and total levels played, and in level-specific actions.

The impact of class membership on posttest learning outcomes was estimated using the BCH method within MPlus (Asparouhov & Muthen, 2014). We found that students in the high-engagement group scored significantly higher on the post-test than students in the low-engagement group, with a mean difference of over half a point ($X(4) = 15.691$, $p < 0.01$).

4 Discussion and Conclusions

Engagement is important to learning both within educational games, and in learning technologies more broadly, but students can engage with the same game in different ways. In this paper, we identify subgroups of students in an educational game context using features drawn from the game log data. We interpret these subgroups in terms of their overall game engagement, and we link subgroup membership to learning outcomes. By using players' process of gameplay, rather than self-reported measures, we hope to explicitly link engagement to the actions taken within the learning context (Fincham et al., 2019).

In this study we found a single 'engaged' group, where previous work was able to differentiate between achiever students who were engaged by tangible rewards for achievement, like coins and badges, and explorer students who were engaged by exploring the rules and bounds of the game environment. There are several reasons that this finding may have failed to replicate. First, our sample was relatively underpowered for this type of analysis. Second, Physics Playground has undergone multiple design changes since 2017, and it's possible that these design changes have subsequently changed the ways that students are able to interact with the game. We also found that engaged students outperformed disengaged students on a posttest measure of physics understanding. While engagement in educational tasks has already been shown to strongly influence eventual learning outcomes, we think it's important to construct engagement in the game task as a multivariate measure of an individual's experiences within the game.

The measurement and analysis of engagement profiles represent a valuable means of informing game designers and educators on the behavioral patterns of educational game players, and how those behavioral patterns may be used to drive eventual learning (Ruiperez-Valiente et al., 2020). In this work we have demonstrated that Latent Profile Analysis can be used to generate player typologies that align with overall game engagement, and that these typologies are predictive of posttest performance. Given the increasing breadth and depth of educational games, we hope that analyses such as the one presented here see continued use in determining the best methods for engaging, supporting, and instructing learners in educational game contexts.

References

1. Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Using the BCH method in Mplus to estimate a distal outcome model and an arbitrary secondary model. *Mplus web notes*, *21*(2), 1-22.
2. Bartle, R. (1996). Hearts, clubs, diamonds, spades: Players who suit MUDs. *Journal of MUD research*, *1*(1), 19.
3. Fincham, E., Whitelock-Wainwright, A., Kovanović, V., Joksimović, S., van Staalduinen, J. P., & Gašević, D. (2019). Counting clicks is not enough: Validating a theorized model of engagement in learning analytics. In *Proceedings of the 9th international conference on learning analytics & knowledge* (pp. 501-510).
4. Jung, T., & Wickrama, K. A. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and personality psychology compass*, *2*(1), 302-317.
5. Muthén, L.K. and Muthén, B.O. (2017). Mplus User's Guide. Eighth Edition. Los Angeles, CA: Muthén & Muthén
6. Ruiperez-Valiente, J. A., Gaydos, M., Rosenheck, L., Kim, Y. J., & Klopfer, E. (2020). Patterns of engagement in an educational massively multiplayer online game: A multidimensional view. *IEEE Transactions on Learning Technologies*, *13*(4), 648-661.
7. Shute, V. J., Almond, R. G., & Rahimi, S. (2019). Physics Playground (version 1.3)[computer software]. *Tallahassee, FL: Retrieved from https://pluto. coe. fsu. edu/ppteam/pp-links*.
8. Shute, V. J., Smith, G., Kuba, R., Dai, C. P., Rahimi, S., Liu, Z., & Almond, R. (2021). The design, development, and testing of learning supports for the Physics Playground game. *International Journal of Artificial Intelligence in Education*, *31*(3), 357-379.
9. Slater, S., Bowers, A. J., Kai, S., & Shute, V. (2017, July). A Typology of Players in the Game Physics Playground. In *DiGRA Conference*.
10. Williams, D., Yee, N., & Caplan, S. E. (2008). Who plays, how much, and why? Debunking the stereotypical gamer profile. *Journal of computer-mediated communication*, *13*(4), 993-1018.