A Typology of Players in the Game *Physics Playground*

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ABSTRACT
Educators are increasingly using games as a method for enabling engagement and learning in students, but research has suggested potentially inconsistent outcomes for the use of these digital tools. One explanation for these mixed findings may be different preferred playstyles of game players, such as Bartle's (1996) player taxonomies. This research uses latent class analysis (LCA) as a means of examining similarities across student play interactions, using log data obtained from student actions in a game environment. Our research identified at least three groups of players who play the educational physics game *Physics Playground* – achievers, who obtain a higher number of awards in the game; explorers, who focused on constructing and tinkering with elaborate machines and contraptions; and disengaged players, who seemed to find little content in the game that attracted their attention. Improvements to the existing research methodology and future directions for research are discussed.

Keywords
Typology, playstyle, education, mixture models

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INTRODUCTION

Games (and other game-like digital media, such as interactive simulations and augmented reality) are increasingly used by educators in both formal and informal learning environments (Bowers & Berland, 2013; Yoon et al., 2014; Steinkuehler, Squire & Barab, 2012) yet researchers have struggled with finding consistent improvements in learning and engagement among students (Annetta et al., 2009; Young et al., 2012). This inconsistency could stem from an insufficient understanding of the different interaction styles that learners employ with games and other interactive digital media (i.e. Dickey, 2005). Game environments are much deeper and more complex than traditional forms of instruction (Gee, 2008), and players may show preferences for specific patterns of interactions that are afforded by some game environments but stifled by others. In this paper we develop a player typology framework that describes the different playstyles of students playing the educational physics game *Physics Playground* (Shute & Ventura, 2013).

Multiple typology frameworks have been proposed that attempt to identify different groups of game players, each with their own motivations, goals, interests, and preferences for interacting with game environments. The idea of a typology of game players was first advanced by Richard Bartle (1996), who used his experience in curating early forms of online Multi-User Dungeons (MUDs) to place players into four distinct groups: 'Achievers', characterized by the pursuit of goals and rewards; 'Explorers', characterized by the pursuit of knowledge and understanding of the game, both in terms of the base game (map locations, secrets, etc.) and the metagame (details about the physics engine, loot tables, etc.); 'Socializers', characterized by the pursuit of meaningful relationships with other player characters, including role-playing; and 'Killers', characterized by the pursuit of 'imposing' oneself on other player characters (generally in a less pro-social way than a socializer might). These four typologies lie on two axes: interactions with game content, which achievers and explorers seek out, and interactions with other human players, which socializers and killers seek out.

More recently, researchers have utilized and expanded potential player typologies further by employing quantitative methodologies using surveys, aggregate game data, and other data sources. Research by Nick Yee used principal component analysis (PCA) to mathematically identify player typologies based on self-report survey responses (Williams, Yee & Caplan, 2008; Yee, 2006). Analysis of 3,000 questionnaires submitted by players of popular MMORPGs revealed a ten player typology. These ten player subgroups were then organized into three larger groups: 'achievers' and 'socializers', similar to Bartle's original definitions, and also 'immersion' players, who seek customization and immersion, or escape from real-life problems. In Yee's typology, the explorer group is broken up, with players who enjoy developing an understanding of game rules and mechanics being folded into the achiever group. This would include players like the min-maxer, who try to find the "best" way of playing a game. The other half of the explorer group, the explorer who plays for discovery and hidden secrets, is folded into the immersion player profile. This would include players who like to engage with the lore of the game. Similarly, the killer profile from Bartle's original typology is placed entirely within the achiever group, and killers are portrayed as players for whom competing against and defeating other players is a goal.

Yee's typology was notable for increasing the sample size of players from roughly n=30 players for Bartle's original typology to thousands of players, and for taking a mathematically rigorous approach to the problem. However, since only players of

MMORPGs were surveyed, there was the possibility that these typologies were not true player typologies, but simply MMORPG typologies. Research by Kahn et al. (2015) addressed this concern by validating typologies between genres and cultures. Using the Multiplayer Online Battle Arena (MOBA) *League of Legends* (Riot, 2009) and the Chinese MMORPG *Chevalier's Romance Online 3* (KingSoft, 2009), Kahn collected questionnaire data from 37,446 total players and used a factor analysis approach to identify six different player typologies – socializer, completionist, competitor, escapist, story-driven, and smarty-pants. The first four are relatively familiar, and consistent with characterizations of socializers, killers, achievers, and explorers in Bartle's original typology. 'Story-driven' characters are players who enjoy reading, seeing, and being a part of stories and narratives, and smarty-pants characters are players who seek out gameplay as a means of increasing their intellect and becoming smarter.

Research by Yee and Kahn et al. suggests that there is a reasonable degree of consistency among player typologies across genres as well as cultures, but questions remain around typologies that may exist within single-player games, where interaction styles of killers and socializers may be limited or even non-existent. Additionally, existing research on player typologies relies heavily on self-report data and does not examine player interaction styles directly, such as through server logs. There is no guarantee that players are accurately representing their playstyles, and may be subject to demand characteristics or other social biases in responding to these surveys (Duckworth & Yeager, 2015). Finally, existing research has utilized statistical techniques designed to account for and explain variability in data, but not necessarily to identify latent subpopulations within a sample (such as subcategories of particular playstyles in a group of gamers).

In the present study we examine a typology of players within the single-player educational physics game *Physics Playground*, using a latent class analysis (LCA) modeling approach. LCA (McCutcheon, 1987; 2002; Masyn, 2011; Samuelsen & Raczynski, 2013) is a "person-centered" analytic technique that considers the covariance structure of variables across cases (players) as a way of assigning group membership to individuals, rather than observing patterns among groups of variables. Therefore, we believe that LCA is well-suited to describing the differences that exist in a player's preferences for and patterns of interaction within gameplay. We use latent class analysis to measure the covariance structure of aggregate variables collected from logs of actual player gameplay over time, rather than self-reported questionnaire data. This distinguishes the current research from efforts that have come before it – rather than collecting post-hoc survey data from players, we use their actions and behaviors within the game to categorize them into different subgroups.

METHODS

Data for the study were collected through the *Physics Playground* physics game (Kai et al., 2015). In *Physics Playground* players draw simple machines such as levers, pendulums, pulleys, and ramps in order to move a ball to a red balloon. Players are awarded badges based on the number of attempts taken to complete a level and the sophistication and quantity of machines used. Game data consisted of complete player interactions with the game environment, including game-generated data (summary reports, position of player-created elements, time-stamped level start and end times), player-generated data (player actions, keystrokes, and creations) and automatically-generated data (type of machine constructed by the player, aggregate statistics). Data were collected from 138 unique players, and included 2748 unique player-level pairings (i.e. player 5 on level 3) drawn from over 6 million individual player actions.

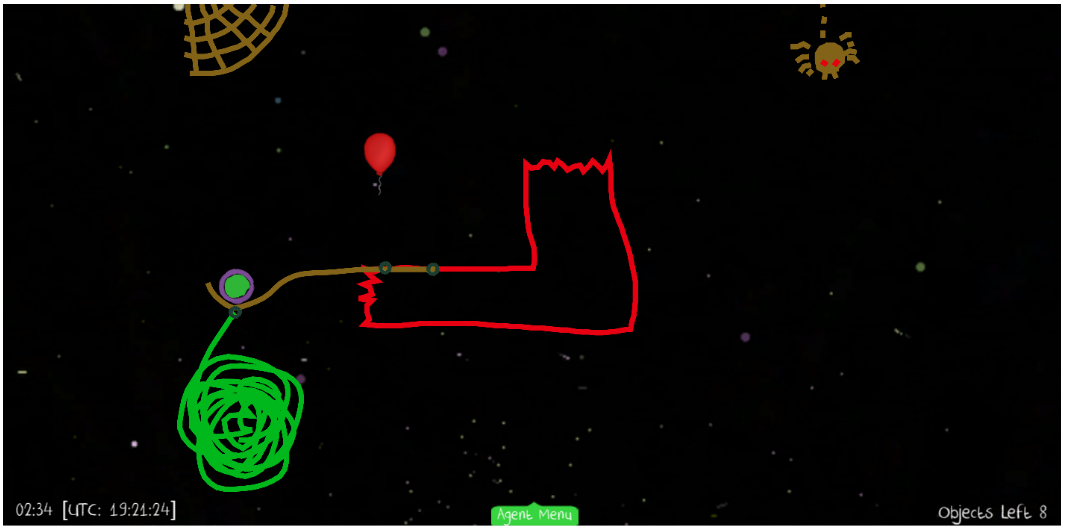

Figure 1: *Physics Playground* gameplay screenshot. A scoop with a weight attached is being used to catapult the green ball towards the red balloon.

To better describe player typologies as a function of overall behaviors, data were aggregated such that one row of data represented the complete actions of one player across all levels. We included or excluded particular variables from the model according to two criteria:

(1) The variable was a likely indicator for an existing player typology within the literature (such as medal earning as a marker for achievement),
(2) The variable was a likely indicator of differences in play style within *Physics Playground's* interaction space (such as the use and frequency of freeform drawings)

By selecting criteria that are both potential markers for existing typology theories as well as criteria that are representative of the varying approaches players can employ within *Physics Playground*, we constructed a model that both maps onto existing typology research as well as captures the variance and differences among players of *Physics Playground* specifically.

A latent class analysis was conducted using the analysis software MPLUS 7.11 (Muthen & Muthen, 2007). Complete input for MPLUS can be found in Appendix A. Figure 2 specifies the full LCA model used. For greater interpretability, all variables used in the model were standardized. We included three variables involving the number and quality of badges earned by players: gold badges earned (badgeg), silver badges earned (badges), and no badge earned (badgee). In *Physics Playground* each level has one or several recommended machines for completing the level. If a player uses one of these machines (such as a lever, pulley, or pendulum) to complete the level, they receive a silver badge for that machine. If a player uses one of these machines **and** the total number of objects used to create the machine is less than the "par" of the level, the player earns a gold badge. Completing a level by using a machine other than what is recommended by the level does not earn the player any badges. We also included three variables that describe the process of drawing within a level: machine drawings (machines), freeform drawings (drawfree), and erasures (erase). Machine drawings are objects that a player creates which are recognized as a simple machine by the game. Freeform drawings are anything else that the player draws (such as doodles or small sticks to nudge the ball). Erasures are events where a player removes a previous drawing. We also included the number of total levels that a player entered (levstart), including duplicate levels, the number of times that players restarted a level (restart), and the total number of events (drawings, menu actions, starts and restarts) that the player logged (totevent). These variables were selected on the basis of either describing existing typology facets (such as badges for achievers) or describing important dimensions of the affordances and goals of the game space (such as erased objects and level starts).

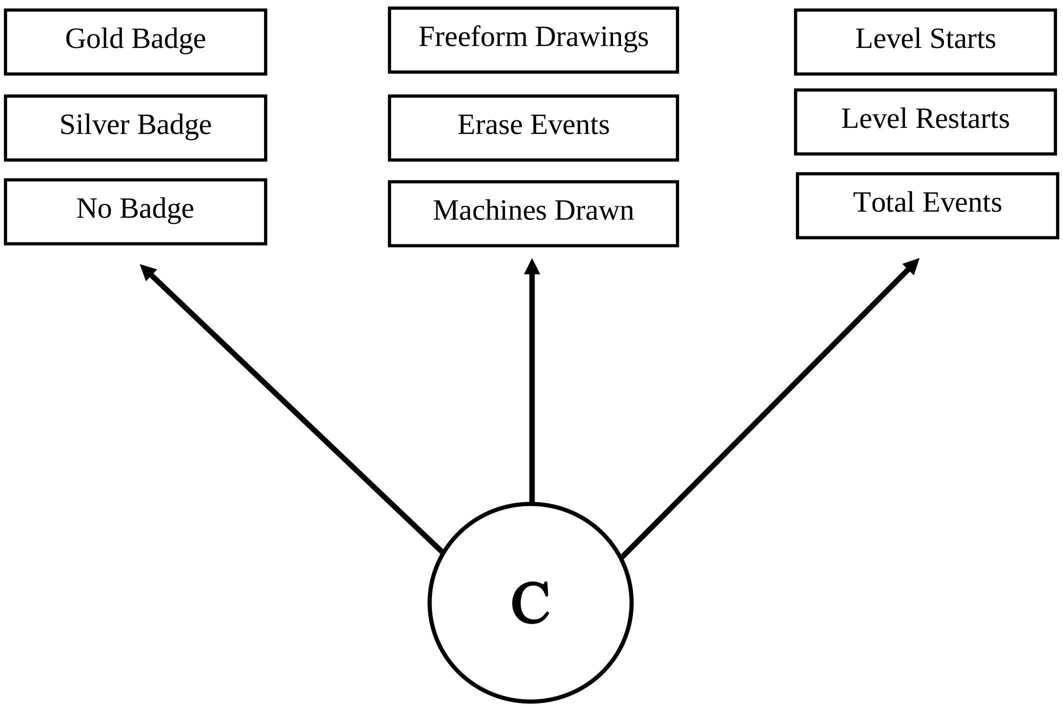

Figure 2: The latent class analysis model used in the analysis.

RESULTS

Following recommendations from current work in the field, a series of LCA models were constructed to evaluate model goodness of fit along multiple metrics (Asparouhov & Muthén, 2007, 2014; Boyce & Bowers, 2016; Graves & Bowers, in press; Jung & Wickrama, 2008; Lo, Mendell & Rubin, 2001; Nylund & Vermunt, 2010). We followed current recommendations in model fitting in the LCA methods literature, and fit an iterative set of models. That is, we first started with two latent class subgroups, assessed model fit, and then continued to fit models with additional k+1 latent classes, assessing model fit until the BIC minimum was reached (Table 1). As the research in fitting LCA models is an area of active investigation (Asparouhov, & Muthén, 2007; Masyn, 2011; Nylund, Samuelsen & Raczynski, 2013), we provide the recommended fit statistics in Table 1. While the minimum BIC of the model was reached at ten latent classes, the other model fit statistics did not indicate a strong fit, including LMR. Additionally, all models greater than three latent classes produced solutions with poor fit as the LMR was not significant and multiple subgroups had less than 10% of the sample, most likely due to overall low power (Dziak, Lanza, & Tan, 2014). Thus we opted for the more parsimonious three class solution as the overall fit of the model was good, mis-specification was low with less than 8% of any of the cases cross-classified, and the BLRT (Bootstrapped Likelihood Ratio Test) was significant ($p < 0.001$).

Model	AIC	BIC	-Log Likelihood	LMR Statistic	p	Entropy
C = 2	3374.38	3456.343	1659.19	193.307	0.0731	0.933
C = 3	3238.836	3350.071	1581.418	152.450	0.1633	0.856
C = 4	3178.175	3318.683	1541.088	79.056	0.4653	0.889
C = 5	3133.589	3303.369	1508.794	63.302	0.5388	0.911
C = 6	3089.521	3288.574	1476.76	62.794	0.4754	0.923
C = 7	3044.468	3272.794	1444.234	63.759	0.3241	0.916
C = 8	3001.667	3259.265	1412.833	62.137	0.7458	0.923
C = 9	2954.366	3241.237	1379.183	66.590	0.5394	0.927
C = 10	2925.038	3241.181	1354.519	48.807	0.8057	0.924
C = 11	2898.144	3243.560	1331.072	46.398	0.3721	0.925

Table 1: Fit statistics for the latent class analysis models.

While we interpret the three class model below, we also provide the descriptive statistics for both the two and three class models, as the fit statistics between the two models are similar and LCA models with more classes can at times provide a hierarchy of nested latent classes that can aid in interpretability (Bauer & Curran, 2003; Boyce & Bowers, 2016).

Two Class Model

The results for the two class model are displayed in Table 2. Variables that are statistically significant in the table are variables which characterize one group versus all others; variables that are not statistically significant do not differentiate members of one class from members of another. Additionally, all variables were standardized before they were used in the model. Therefore, results are interpreted as the number of standard deviations above or below the mean that a particular class scores, on average. For example, in the two class model, achievers earned about one standard deviation more gold badges than other players. We characterized the two classes identified by this model as “achievers” (n = 23, 16.67% of players) and “other players” (n = 115, 83.33% of players). Achievers appeared to be motivated by the attainment of badges within the game, obtaining significantly more gold and silver badges than the other players, and playing more levels overall. Achievers also produced more freeform drawings, and recorded more actions and events within the system. Surprisingly, the “achiever” group was also characterized as drawing less machines than the other players. This could be due to the achievement-oriented players drawing fewer (but more productive) machines, while other players drew more machines that failed to complete levels. Other players were largely characterized by the existence of the achiever group. They earned fewer gold badges than the achievers, and recorded fewer levels without earning a badge (which would happen when the player does not use a machine appropriate for the level), but played fewer levels overall. All of these variables are instances where the achievers were scoring quite high, and we believe that this two-class typology is best characterized as players who are achievers versus everyone else playing the game.

	Achievers (n = 23)			Others (n = 115)		
Variable	Mean	S.E.	*p*	Mean	S.E.	*p*
badgee	1.681**	0.409	< *0.001*	-0.370 **	0.070	< *0.001*
badges	0.502	0.344	0.144	-0.111	0.131	0.397
badgeg	0.931*	0.425	*0.029*	-0.205 **	0.068	*0.003*
machines	-0.267*	0.130	*0.040*	0.059	0.101	0.559
drawfree	0.467*	0.224	*0.037*	-0.103	0.103	0.319
erase	-0.161	0.267	0.545	0.036	0.100	0.721
levstart	1.618**	0.247	< *0.001*	-0.356 **	0.103	*0.001*
restart	0.346	0.356	0.331	-0.076	0.089	0.392
totevent	0.492**	0.175	*0.005*	-0.108	0.111	0.329

Table 2: Parameters for the two class model. Results significant at $p < 0.05$ are denoted with *, results significant at $p < 0.01$ are denoted with **.

Three-Class Model

Table 3 shows the results for the three class model, and Figure 3 plots the group means. We characterized the three classes identified by this model as "achievers" (n = 24, 17.39% of players), "explorers" (n = 70, 50.73% of players), and "disengaged players" (n = 44, 31.88% of players). Achievers in the three class model were extremely similar to those in the two class model – they were characterized by high counts of earned gold medals, more levels, but fewer drawn machines. The three class model also identified "explorer" players. This group of players was characterized by a higher proportion of silver badges earned, higher numbers of drawings and erases, and a higher number of events logged overall than players from other groups. Players classified as explorers, or "tinkerers", are building and revising complicated machines, and are not particularly concerned with the attainment of badges (they are earning more silver badges for level completion, but are not pursuing gold badges). Finally, the three class model classified disengaged players, who show decreased engagement across all of the features represented in the model. Disengaged players earn fewer badges, start fewer levels, and draw fewer objects than players in other groups.

	Achievers (n = 24)			Disengaged (n = 44)			Explorers (n = 70)		
Variable	Mean	S.E.	*p*	Mean	S.E.	*p*	Mean	S.E.	*p*
badgee	1.766 **	0.232	*<0.001*	-0.518 **	0.104	*<0.001*	-0.239*	0.106	*0.024*
badges	0.447	0.238	0.060	-0.905 **	0.245	*<0.001*	0.459*	0.198	*0.021*

badgeg	1.047	**	0.373	*0.005*	-0.265	**	0.098	*0.007*	-0.170	0.102	0.094
machines	-0.300	*	0.136	*0.028*	0.076		0.208	0.715	0.049	0.122	0.057
drawfree	0.430		0.256	0.093	-0.788	**	0.250	*0.002*	0.386*	0.203	*0.017*
erase	-0.236		0.228	0.301	-0.618	**	0.211	*0.003*	0.493*	0.208	*0.018*
levstart	1.679	**	0.197	<*0.001*	-0.876	**	0.178	<*0.001*	0.030	0.143	0.836
restart	0.374		0.297	0.207	-0.131		0.248	0.598	-0.037	0.171	0.830
totevent	0.460	*	0.205	*0.024*	-0.814	*	0.326	*0.013*	0.394*	0.165	*0.017*

Table 3: Parameters for the three class model. Results significant at $p < 0.05$ are denoted with *, results significant at $p < 0.01$ are denoted with **.

We believe that this model is most representative of Bartle's original four subgroup typology. There are clearly defined achiever and explorer groups, while killers and socializers are likely classified together as the disengaged subgroup due to the single-player nature of the game. The achiever and explorer groups diverge along the pathways that we expected them to according to Bartle's original typology – namely, achievers engage with in-game performance metrics and explorers engage with game mechanics and exhibit tinkering behavior.

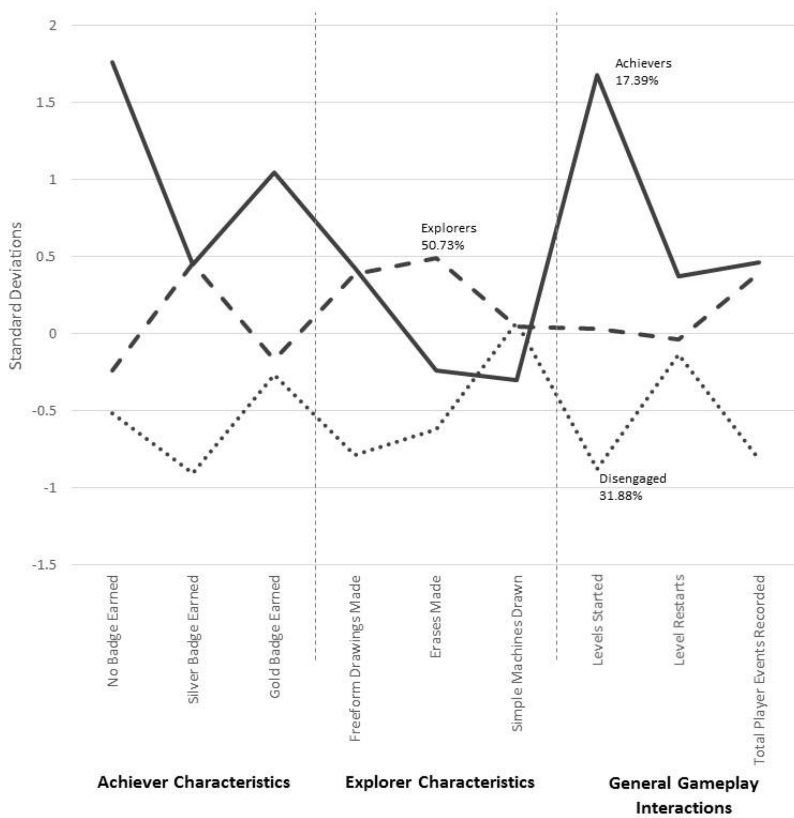

Figure 3: Indicator plot for the three class typology. Disengaged players (31.88% of players overall) maintain low levels of interaction with all facets of the game. Achievers (17.39% of players overall) engage highly with the badging system, earning many more

of them and playing many more levels. Explorers (50.73% of players overall) spend their time drawing and revising machines, and do not seek out the optimal solutions to levels.

CONCLUSIONS

In this paper we constructed a latent class analysis model using player log data from the game *Physics Playground*, in an effort to develop a typology of player styles in games. Our data suggests that there are at least two types of players within our data, and provides support for three types of players that align with how Bartle's typology would manifest in a single-player game. "Achiever" players are strongly motivated by earning in-game rewards such as badges, while "Disengaged" players did not engage as deeply with game content, perhaps because they were not able to interact with the game in their preferred way. "Explorer" players eschewed earning gold badges in favor of building and revising complex machines and contraptions for exploring the mechanics of the game. We present the three-class model because we believe that it maps more closely to Bartle's original typology, but we also present the two-class model because it has better statistical fit given the limited size of our dataset. While more subgroups within this typology may exist, and have been theorized to exist in the literature, our capacity to identify these additional typologies with this modeling framework is limited by several factors.

The first limitation with the current research framework is sample size. Our analyses used data on 138 players across nine facets of play. Such a dataset is only capable of detecting very large effects (Dziak, Lanza & Tan, 2014). Therefore, our analyses detected achievement-oriented players because they most differentiated themselves in this game context, but other more subtle differences between players were more difficult to detect in our data. While BIC criterion fitting suggested as many as ten unique classes in the data, these classes were often fit to very small outlier cases, some as small as a single player. More robust LCA solutions created in this style will require additional data, with thousands of players represented. These larger datasets would afford greater flexibility in the variables used by the model as well. Future work on player typologies could synthesize real-time measures of student affect, such as those developed by Bosch et al. (2016), to determine not just how different groups of players engage with a game, but how players themselves experience the game at an affective level.

Second, using game environments which do not afford interpersonal contact and interaction may make typology construction difficult. Players who seek to engage with a game through interpersonal actions may be disengaged by a game which does not offer these interactions, or they may seek out a less-preferred interaction style. It is interesting to note that *Physics Playground* is a game about the creation and exploration of physics principles using simple machines – the context of the game aligns naturally with the explorer group of players. Coincidentally, explorers comprised more than half of the three-class model. Some killers and socializers may have made the decision to engage with the most salient features of the game, since they were unable to engage in the styles that they preferred. To more completely construct a typology of game players, a sample which examines the same players across multiple game contexts (both single-player and multi-player) is required.

Overall, our model suggests considerations for games researchers and developers interested in developing environments which afford productive interactions and engagement in players. Our research shows patterns of disengagement among a certain group of players, perhaps because of the lack of socialization and human interaction available in this particular game environment. Future studies in typology and game design may seek to consider the best avenues of participation for players from each typology, and use these avenues as design recommendations for enhancing interest and engagement in players.

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