

# Modeling Motivation in a Social Network Game Using Player-Centric Traits and Personality Traits

Max V. Birk<sup>1</sup>(✉), Dereck Toker<sup>2</sup>, Regan L. Mandryk<sup>1</sup>, and Cristina Conati<sup>2</sup>

<sup>1</sup> Department of Computer Science, University of Saskatchewan,  
110 Science Place, Saskatoon, SK S7N 5C9, Canada  
{max.birk, regan.mandryk}@usask.ca

<sup>2</sup> Department of Computer Science, University of British Columbia,  
2366 Main Mall, Vancouver, BC V6T 1Z4, Canada  
{dtoker, conati}@cs.ubc.ca

**Abstract.** People are drawn to play different types of videogames and find enjoyment in a range of gameplay experiences. Envisaging a representative game player or persona allows game designers to personalize game content; however, there are many ways to characterize players and little guidance on which approaches best model player behavior and preference. To provide knowledge about how player characteristics contribute to game experience, we investigate how personality traits as well as player styles from the BrianHex model moderate the prediction of player motivation with a social network game. Our results show that several player characteristics impact motivation, expressed in terms of enjoyment and effort. We also show that player enjoyment and effort, as predicted by our models, impact players' in-game behaviors, illustrating both the predictive power and practical utility of our models for guiding user adaptation.

**Keywords:** User modeling · Personality · Player experience · Social network game · Linear regression · Moderation · Motivation

## 1 Introduction

Game designers often envisage a representative player of their game, and can benefit from making design decisions with this illustrative player in mind. These archetypal players – or ‘player personas [6] – can be created from many factors, including demographic characteristics (e.g., age, sex), expertise with a system (e.g., novices), gameplay goals or aspirations (e.g., to pass the time), personality traits (e.g., extroverted), or what motivates a player to enjoy a game (e.g., sensation seeker). Player-centric models can help designers tailor their games to a specific type of player with specific play preferences. For example, Orji et al [18], showed that tailoring serious games for health to specific player types may increase their efficacy.

Although there are different approaches for characterizing players, there is little knowledge about which characterizations are most informative for predicting player experience and for guiding design decisions accordingly. For example, the five-factor model (FFM), an approach of describing personality according to five traits [14], is a

robust and well-studied model; however, personality has not been shown to be consistently effective in predicting player experience [e.g., 5,12,13,21,27]. In an attempt to uncover candidates for “robust traits that could be used for a player instrument” [3], Bateman and Nacke created the BrainHex model [17], which characterizes people along seven dimensions specific to the game play experience (Achiever, Conqueror, Mastermind, Daredevil, Survivor, Seeker, Socialiser). Although BrainHex has successfully been used in some game studies (e.g., to model how different types of players respond to various persuasive strategies in serious games [18]), it is not as stable, as theoretically grounded, or as well studied as the FFM.

The goal of this paper is to provide a better understanding of if and how player personality and the BrainHex player-centric traits can serve as characterizations of player experience to guide personalized game design. Similar to previous work [e.g. 5,16, 22,24], we characterize player experience in terms of invested effort and enjoyment in game play, two key aspects defining a player’s intrinsic motivation to play, a well-established construct for evaluating player experience [5]. We then build models to ascertain how personality and player-centric traits interact with known predictors of invested effort and game enjoyment: satisfaction of needs such as competence, autonomy, relatedness, presence, and intuitive control [24]. Investigating the moderating effect of personality traits and player typologies on well-established player experience measures – i.e., need satisfaction and intrinsic motivation – is important to understand how individual differences enhance or diminish the experience of playing a video game. With a personalized understanding of player experience, designers could create engaging experiences tailored to a specific play style, and consider individual needs/interests to create more compelling experiences.

To build the models, we collected data from over 3400 players of the social network game Pot Farm (Eastside Games Studio, 2010). Social network games are games played online that take advantage of a player’s social network, supporting the impulsive use of social network services [19]. We collected player-centric and personality traits along with validated measures of player experience [24] and logs of in-game behaviors. A moderated regression analysis [11] based on this data shows that both FFM and BrainHex factors impact the well-established influence of need satisfaction on player enjoyment and effort, showing that these traits should be considered in combination with the satisfaction of needs to predict player motivation in game play. Furthermore, we show that our models can also predict in-game player behavior.

The importance of our results is two-fold. They contribute to our understanding of game and play experience, adding richness to the theoretical models of player characterization that can be leveraged for more informed, personalized game design. They also reveal how differences in player experience are reflected in players’ in-game behaviors. These findings are important for designing adaptive game elements aimed at improving player motivation, since they can help identify which behaviors are worth encouraging for which users in real-time during game play.

## 2 Related Work

The use of player archetypes to describe a fictional and representative player derives from the persona framework developed by Cooper [7] in the context of

human-computer interaction, in which personas are described as detailed user archetypes to inform a product's design. Applying this approach to play, Canossa and Drachen [6] created play personas, defined as “[...] clusters of preferential interaction (what) and navigation (where) attitudes, temporally expressed (when), that coalesce around different kinds of inscribed affordances in the artifacts provided by game designers”.

Player-centric models are new approaches to differentiate player preferences and help designers to build games addressing a diverse audience. Different typologies have been proposed to classify players. One of the first was Bartle's Test of Gamer Psychology [2], which divides players into four classes: killer, achiever, socializer, and explorers [1]. Building on Bartle's work, Yee et al. [31] applied principal component analysis (PCA) to survey data and identified Achievement (finding enjoyment in progression and completion), Social (the enjoyment of socializing in the game world), and Immersion (finding enjoyment in dwelling in a game environment) as the three driving factors of motivation in Massively Multiplayer Online Role-Playing Games.

Integrating concepts from previous methodologies, the BrainHex model [17] distinguishes between 7 types of players: *Achievers* are goal-oriented and are motivated by completing tasks or collecting things. *Conquerors* enjoy defeating difficult opponents, and overcoming challenges. *Daredevils* are excited by the thrill of taking risks and enjoy playing on the edge. *Masterminds* enjoy solving puzzles, and devising strategies. *Seekers* enjoy exploring things, sense-stimulating activities and discovering their surroundings. *Socialisers* enjoy interacting with others. *Survivors* love the experience associated with terrifying scenes and the thrill of escaping from scary situations. Based on the BrainHex questionnaire [4], players are characterized by how much they associate with each of the groups. There is promising evidence that this model can be leveraged to understand the connection between player type and experience; for instance, it was successfully used to model how different types of players respond to various persuasive strategies in serious games [18].

Whereas player-centric models are specific to video games, researchers have also investigated player models built on the more general construct of personality. Most of this work relied on the well-established Five Factor Model of personality, (FFM) [14], which categorizes personality types along the five dimensions of Extraversion, Neuroticism, Agreeableness, Conscientiousness, and Openness. For instance, Johnson et al. [13] showed that conscientiousness is negatively correlated with flow, suggesting that planning and goal orientation might interfere with the flow experience in games. The relevance of personality for genre preference is also under investigation: Peever et al. [20] demonstrate that personality can be used to predict player preference for certain genres, whereas Park et al. [20] found the opposite. It is still an open question how personality can be leveraged to improve player modeling. However, research on player motivation and personality indicates relevance for Games User Research (GUR) and the evaluation of player experience [5,20].

A few efforts have been made to compare personality and player-centric models (e.g., [16,17]), however, there is no clear indication of which is more relevant to predict player experience [23]. We perform a moderation analysis [11], with the established link between need satisfaction and player motivation, operationalized as

enjoyment and effort, moderated by personality (FFM) and player type (BrainHex). The original aspect of our work is that we explore if and how player traits models moderate the effect of well-known predictors of effort and enjoyment associated with the satisfaction of a variety of player needs: autonomy (accepting challenge under one's own volition); competence (experiencing success and failure based on one's own skills); relatedness (experiencing relations to others); presence (a sense of immersion in the game) and intuitive control (the natural mapping of control to action) [24].

### 3 Data Collection and Modeling

In order to carry out our evaluation of player type and personality in terms of game-play enjoyment, we leveraged a real-world case study using an established online social game. The players in our data set were gathered from the free-to-play Facebook game 'Pot Farm', which currently has over 600,000 monthly active users. Pot Farm is a marijuana-themed 'Ville style farming simulation where users plant and harvest crops, complete quests, collect gold, and level up (see [26] for an overview of 'Ville style design patterns, and themes). We chose a farming simulation because it is among the most popular types of social network games [25].

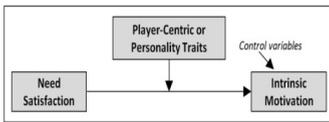
We administered surveys to Pot Farm players over one week using a mechanism that prompted players via an in-game pop-up message. Players could complete the survey for a reward of in-game content or they could decline. To ensure broad coverage, surveys were administered randomly across several ranges of play-experience – from brand new players to those who had been playing the game for several months; however, survey respondents had to have played the game at least once within the past week. We also collected data on age, sex, and level, as well as game-based attributes (i.e., telemetry) of game events such as coins, quests, and achievements.

Players were surveyed using the following validated scales: *Player-Centric Traits* were measured using the 21-item BrainHex instrument [4]. *FFM Personality Traits* were assessed using the Ten-Item-Personality-Inventory (TIPI) [10], which has been used in games research [12]. *Enjoyment and Effort* were assessed using the 5-item and 4-item subscales interest-enjoyment and effort-importance of the intrinsic motivation inventory (IMI) [15]. *Need Satisfaction* was assessed using the 21-item Player Experience of Need Satisfaction (PENS) questionnaire [24].

For each user, we recorded in-game actions logged during their time spent playing Pot Farm. The game events are reported as daily totals, and because the amount of play-time varied across users, we take the average over the last five played days (for new users it consists of the values for their first day of play). The set of play experience items we consider are: neighbour visits (i.e., farms visited of Facebook friends who also play Pot Farm), social claims (i.e., claiming the reward for an advanced achievement that a neighbour has achieved), logins, coin events (i.e., coins added to the player's inventory), quests completed (i.e., in-game tasks completed), achievements unlocked (i.e., completion of a more or less difficult series of tasks), and contraptions (i.e., objects created by combining other in-game items).

We obtained 3486 completed surveys; however, 1477 participants were removed if 3 or more of their factors were 2 standard deviations from the mean, or if they had zero variance across a construct. We removed more than 40% of the original sample from our analysis to remove participants who clicked through the questionnaires without considering the answers in order to quickly earn the premium currency reward for survey completion. The majority of removed participants was due to zero variance across the survey, which indicates that the response to each item was the same within and between constructs, e.g. indicating “strongly agree” to all items independent of the survey questions (e.g., “I enjoy the game very much”, “The game does not hold my attention”). Next, we randomly subsampled remaining players across different amounts of play-time to produce an even distribution across player experience. For the resulting 1172 participants, each attribute is z-standardized [9], to allow for comparisons between scales across and within models. Ages of the 1176 players (33.9% female) ranged from 18 to 65, with the majority (33.1%) being 18-24.

Because the link between need satisfaction and motivation has been established [24], our goal is to see how this link is moderated by personality or player traits. We



**Fig. 1.** Structure of Moderated Multiple Regression Model

use moderated multiple regression analysis [11], which is similar to a traditional multiple regression but includes interactions between pairs of individual predictors. Using SPSS, we constructed 20 models, 10 for each of our motivational factors, enjoyment and effort (*outcome variables*), based on the path diagram show in Figure 1. Each model

consists of one of the five needs, along with either the set of personality traits (FFM) or player-centric traits (BrainHex). These traits appear individually as predictors in the model, and also as moderators with each need satisfaction item. Three *control variables* (age, sex, game level) are also included in all models.

## 4 Results of Moderation Analysis

We organize the presentation of the results by the motivation variables being predicted, i.e., enjoyment and effort. However, we summarize results for the control variables here because they had similar trends across all 20 models. Game level was always the only significant control variable ( $mean-p < .001$ ;  $mean-\beta = .17$ ), with players at higher levels being more motivated.

### 4.1 Predicting Enjoyment

The fit of the models (adjusted  $R^2$ ) and the  $\beta$  values for the moderator (player-centric or personality trait), the predictor, (need), and the interaction between the moderator and the predictor (i.e., the effect of moderation) are shown in Table 1. Each of the 5 need satisfaction predictors (i.e., PENS Item) are always a significant predictor of

enjoyment, with  $\beta$  values that are always positive, confirming previous work that greater satisfaction of any of the five needs predicts higher enjoyment [24].

Player-centric traits show significant main effects on enjoyment across models for mastermind and achiever. Personality traits also show main effects across all models for conscientiousness and openness (see Table 1). These results reveal that two of the personality traits and two of the BrainHex traits have predictive value for player enjoyment. However, most notably there are additional cases where personality or player traits moderate the influence of needs satisfaction on player enjoyment. We follow up on these significant moderation effects with a simple slopes analysis, which considers the regression of the predictor on the dependent measure for low, average, and high levels of the moderating variable [9]. Comparing the slopes in terms of their significance and the value and direction of beta allows us to interpret the moderating influence of traits on the value of needs for predicting motivation. All relevant slopes are depicted in Figure 2.

**Table 1.** Simple and moderated effects on enjoyment. Adjusted  $R^2$  for all effects are presented at the top of each column. *T* = Player Centric Traits; *T\*N* = Moderation of *T* and Need Satisfaction. <sup>x</sup> indicates an effect significant at the .05 level, \* indicates significance at the .01 level, \*\* indicates significance at .001.

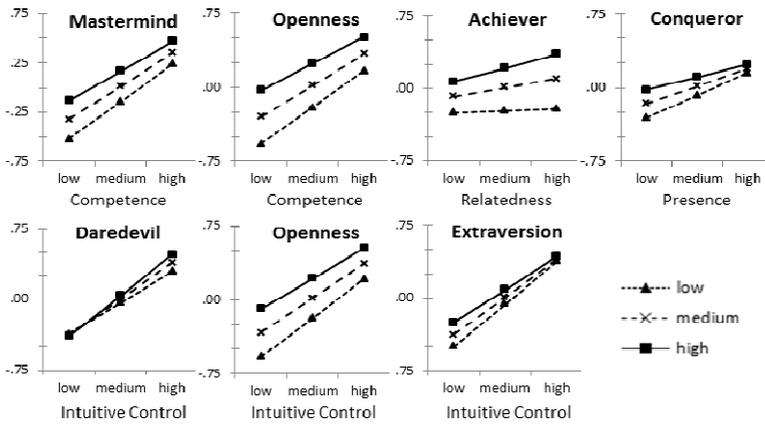
Enjoyment	Competence		Autonomy		Relatedness		Presence		Intuitive Control	
	T ( $\beta$ )	T*N ( $\beta$ )	T ( $\beta$ )	T*N ( $\beta$ )	T ( $\beta$ )	T*N ( $\beta$ )	T ( $\beta$ )	T*N ( $\beta$ )	T ( $\beta$ )	T*N ( $\beta$ )
	Model $R^2$ = 0.22		Model $R^2$ = 0.27		Model $R^2$ = 0.14		Model $R^2$ = 0.16		Model $R^2$ = 0.24	
<i>PENS</i> Item	0.32**	n/a	0.39**	n/a	0.09**	n/a	0.19**	n/a	0.35**	n/a
<i>Seeker</i>	0.07 <sup>x</sup>	0.04	0.05	0.02	0.09*	-0.02	0.09*	-0.03	0.07	0.04
<i>Survivor</i>	-0.02	-0.01	-0.04	-0.04	-0.05	-0.04	-0.07 <sup>x</sup>	0.00	-0.04	-0.03
<i>Mastermind</i>	0.09*	-0.09 <sup>x</sup>	0.10*	0.02	0.14**	0.04	0.14**	0.02	0.09*	-0.03
<i>Conqueror</i>	-0.01	0.07	-0.03	-0.05	-0.02	-0.05	-0.01	-0.08 <sup>x</sup>	-0.02	-0.02
<i>Socializer</i>	0.03	-0.03	0.04	0.01	0.03	0.03	0.03	0.04	0.04	0.03
<i>Daredevil</i>	-0.04	0.00	-0.04	0.01	-0.03	-0.04	-0.04	-0.02	-0.02	0.07 <sup>x</sup>
<i>Achiever</i>	0.16**	0.02	0.16**	0.01	0.17**	0.09 <sup>x</sup>	0.17**	0.06	0.14**	0.00
	Model $R^2$ = 0.23		Model $R^2$ = 0.28		Model $R^2$ = 0.16		Model $R^2$ = 0.19		Model $R^2$ = 0.25	
<i>PENS</i> Item	0.31**	n/a	0.39**	n/a	0.12**	n/a	0.22**	n/a	0.34**	n/a
<i>Extraversion</i>	0.02	-0.01	0.01	-0.01	0.02	0.00	0.03	0.04	0.04	-0.06*
<i>Agreeableness</i>	0.05	0.02	0.06 <sup>x</sup>	-0.01	0.05	0.01	0.07 <sup>x</sup>	0.03	0.06	0.00
<i>Conscientiousness</i>	0.15**	-0.01	0.14**	-0.02	0.17**	0.02	0.16**	0.00	0.13**	0.04
<i>Emotional Stability</i>	0.03	-0.05	0.03	-0.02	0.04	0.03	0.05	-0.03	0.01	0.00
<i>Openness</i>	0.15**	-0.06 <sup>x</sup>	0.16**	-0.02	0.19**	-0.01	0.21**	-0.02	0.14**	-0.05 <sup>x</sup>

**Competence:** There are moderations of mastermind and openness on the influence of competence on enjoyment. For both, the steepness of the slope is higher for people with low value of the traits ( $\beta_{mast}=.38, \beta_{open}=.37, p<.001$ ), as compared to medium ( $\beta_{mast}=.34, \beta_{open}=.32, p<.001$ ), and high ( $\beta_{mast}=.30, \beta_{open}=.27, p<.001$ ). These progressions indicate that competence becomes a weaker predictor of enjoyment as players increase in ratings for mastermind or openness.

**Relatedness:** There is a moderation of relatedness by achiever: Relatedness only predicts enjoyment for medium ( $\beta=.09, p<.001$ ) and high ( $\beta=.15, p<.001$ ) achievers.

**Presence:** There is a moderation of presence on enjoyment by conqueror; the steepness of the slope is higher for low conqueror ( $\beta=.23, p<.001$ ), as compared to medium ( $\beta=.18, p<.001$ ), and high conqueror ( $\beta=.13, p<.01$ ), indicating that presence becomes a weaker predictor of enjoyment as players increase in ratings for conqueror.

**Intuitive Control:** There are moderations of daredevil, extraversion and openness on the influence of intuitive control on enjoyment. The moderations of extraversion and openness are similar: the steepness of the slope is higher for low measures of these traits ( $\beta=.44$  for extraversion,  $\beta=.39$  for openness,  $p<.001$ ), as compared to medium ( $\beta=.39$  for extraversion,  $\beta=.35$  for openness,  $p<.001$ ), and high values ( $\beta=.34$  for extraversion,  $\beta=.31$  for openness,  $p<.001$ ). Thus, intuitive control becomes a weaker predictor of enjoyment as players increase in ratings for extroversion or openness.



**Fig. 2.** Follow up simple slopes analysis for the discovered significant effects of need satisfaction on *enjoyment*, moderated by player traits (refer to Table 1)

Daredevil has the opposite moderating effect on the influence of intuitive control on enjoyment: the steepness of the slope is lower for low daredevil ( $\beta=.33, p<.001$ ), as compared to medium ( $\beta=.39, p<.001$ ), and high daredevil ( $\beta=.44, p<.001$ ); intuitive control is a weaker predictor of enjoyment as players decrease in ratings for daredevil.

**4.2 Predicting Effort**

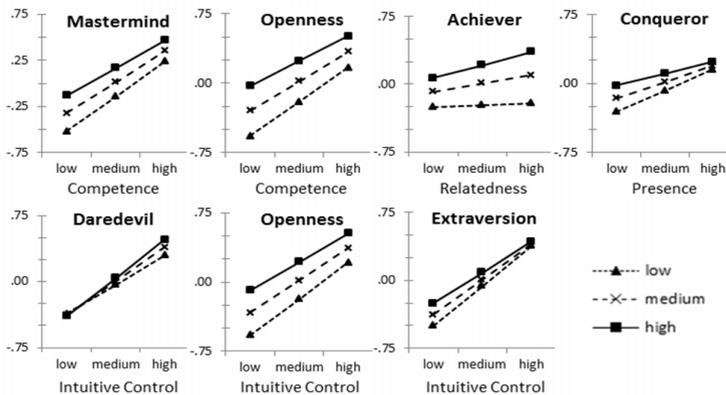
In terms of predicting effort, seven significant moderators were discovered using the same analysis described the previous subsection. Due to space limitations, we only show the final directionalities in Figure 3.

Notably, as was the case for enjoyment, there is no moderating effect of traits on autonomy, but there are effects for the other four needs. These effects, however, involve different traits (with the exception of mastermind on competence) showing that

the two motivational factors of enjoyment and effort should be treated separately when it comes to leveraging player type for personalized game designed.

Our results show two different ways in which personality and player-centric traits moderate the influence of need satisfaction on effort: (1) the trait affects whether or not there is a predictive relationship of need satisfaction on motivation; (2) the relationship is present throughout the models; however, the predictive power of the need changes depending on the level of the player-trait moderator (see Table 1).

We found three examples of the first moderation type: achiever determines whether or not relatedness predicts enjoyment, whereas mastermind and agreeableness predict whether or not relatedness predicts effort. All other moderation effects scale the influence of need satisfaction on the prediction of enjoyment or effort.



**Fig. 3.** Follow up simple slopes analysis for the discovered significant effects of need satisfaction on *effort*, moderated by player traits

### 4.3 Summary of Results for Predicting Motivation

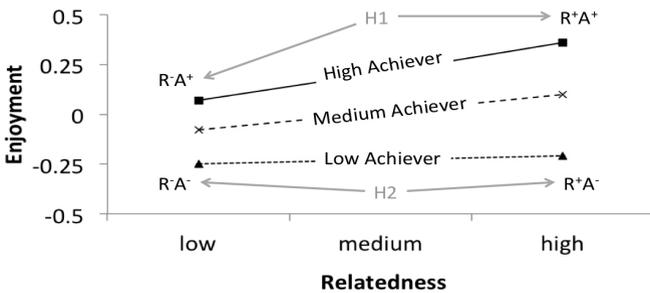
Both types of moderation are interesting because they show how the influence of user traits can identify instances where an increase in need satisfaction does not necessarily lead to a substantial increase in player motivation. This is important because it can guide designers to focus on improving player motivation by meeting the needs of players with specific traits only when it will actually matter (e.g., for improving player motivation, it is worthwhile to understand how to improve relatedness for high achievers, whereas it has no impact on motivation for low achievers).

## 5 How Player Traits are Expressed in Game Data

The models of how player traits moderate the satisfaction of needs on motivation have application beyond contributing to our theoretical understanding. In particular, because we can predict how different players experience enjoyment and effort in games, we should be able to use the models to predict how these various players will express

motivation differences through their in-game behaviors. That is, the models should inform designers on how players will behave in the game as measured through logs of in-game actions. Making this connection would allow for customization of game experience by allowing designers to identify in-game behaviors that are worth encouraging because they are known to increase motivation for certain player types.

To illustrate this point, we apply one of the moderated regression models presented earlier to make hypotheses about how groups of players, differentiated by their traits and their needs satisfaction, behave in the game. We chose the achiever-relatedness-enjoyment model as a representative example from the type (1) of moderated relationships as discussed in the previous section (Figure 4). We created four groups:  $R^+A^+$  were high on both relatedness and achiever ratings;  $R^-A^-$  were low on both relatedness and achiever;  $R^-A^+$  were low on relatedness but high on achiever, and  $R^+A^-$  were high on relatedness, but low on achiever (see Figure 4).



**Fig. 4.** Moderation of the need for relatedness (R), and the player centric trait achiever (A), predicting enjoyment

Because our model predicts that levels of relatedness make a difference only for high achievers and not for low achievers, our hypotheses are:

- *H1. Members of  $R^+A^+$  exhibit more in-game behaviors than members of  $R^-A^+$ .*
- *H2. Members of  $R^+A^-$  will not exhibit more in-game behaviors than  $R^-A^-$ .*

A MANOVA with group (4 levels:  $R^+A^+$ ,  $R^-A^-$ ,  $R^+A^-$ ,  $R^-A^+$ ) as a between-subjects factor on in-game behaviors showed a significant effect of group membership. In particular, there were differences for social claim ( $F_{3,289}=8.8, p<.001, \eta^2=.08$ ), logins ( $F_{3,289}=3.5, p=.016, \eta^2=.04$ ), coin events ( $F_{3,289}=2.9, p=.029, \eta^2=.03$ ), and contraptions ( $F_{3,289}=2.8, p=.038, \eta^2=.03$ ). We used pairwise comparisons with the Holm-Bonferroni correction ( $\alpha=0.05$ ) to test the planned comparisons in our two hypotheses. Table 2 shows a summary of game behavior according to the four groups.

*H1.* As expected, members of  $R^+A^+$  had significantly higher social claims, daily logins, and coin events than members of  $R^-A^+$  (although there was no significant difference in the number of contraptions), confirming H1.

*H2.* As expected, there were no differences in any in-game behavior measures between  $R^+A^-$  and  $R^-A^-$ , confirming H2.

**Table 2.** Mean (m) and standard error (SE) for game data for combinations of high/low achiever and high/low relatedness

<b>Actions (daily sum)</b>	$R^+A^+$		$R^-A^-$		$R^+A^-$		$R^-A^+$	
	<i>m</i>	( <i>SE</i> )						
<b>Neighbour Visits</b>	5	(1.5)	2.7	(0.6)	2.8	(0.8)	2.3	(0.4)
<b>Social Claims</b>	75	(19)	13	(5)	13	(7)	14	(4)
<b>Logins</b>	8.6	(1)	6.4	(0.7)	7.7	(1.2)	5.6	(0.4)
<b>Premium Currency</b>	13	(2)	10	(2)	13	(2)	10	(2)
<b>Coin Events</b>	78	(22)	43	(9)	43	(9)	31	(5)
<b>Quests</b>	4.9	(0.8)	4.5	(0.7)	5.4	(0.9)	5.4	(0.6)
<b>Achievements</b>	0.5	(0.1)	0.5	(0.1)	0.7	(0.1)	0.6	(0.1)
<b>Contraptions</b>	47	(8)	32	(8)	19	(5)	28	(4)

To summarize, our analysis indicates that the moderating influence of player traits on how need satisfaction predicts motivational factors in game play (i.e., enjoyment and effort) can translate directly into in-game behavior of real-world players of a social farming game. In the previous section, we found a moderating effect between achievers, relatedness and enjoyment, showing that there is no increase in enjoyment for low achievers, even when their need for relatedness was satisfied. This lack of difference was also detected by our analysis of the game data (*H2*). Similarly, the moderating effect predicts that for high achievers there is an increase in enjoyment as relatedness is satisfied, and our analysis of game actions allows us to link this increase to differences in specific game actions (*H1*). In particular, we see an increase in social claims for high achievers when relatedness is satisfied. Social claims are of particular interest in this case, because unlike other game events, the underlying mechanism is tied to reciprocal social behavior – it requires having relationships to other players and is comprised of quick social interactions. Achievers are goal-oriented and may use social claims as a means of advancing in the game – however, doing so increases the number of social interactions, potentially increasing the satisfaction of relatedness and ultimately in-game motivation. Our model shows that high achievers with low satisfaction of relatedness also do not have many social claims, perhaps helping to explain their lower in-game enjoyment. As with other Facebook behaviors, social claims are a very lightweight activity that can be considered comparable to an interaction with a loose tie [8], i.e., a quick interaction that still provides value to a relationship between friends. Low achievers, however, have low social claims regardless of their satisfaction of relatedness; it is likely that they draw their enjoyment from other aspects of the game that allow them to satisfy other needs through in-game actions.

Adaptation strategies can be devised based on these results. For example, for high achievers, if few social claims are observed, then additional in-game prompts or quests could be offered to the player to encourage more neighbour visits, which would aid in satisfying their relatedness, thus improving motivation to play the game. Because neighbour visits are not related to enjoyment for low achievers, encouraging this behavior to these players could be intrusive, leading to decreased motivation.

## 6 Discussion and Conclusions

In this paper, we make a theoretical contribution by clarifying the relationship between personality and player-centric traits, and their relevance in explaining how need satisfaction and motivation during game play are facilitated and expressed in an ecologically-valid video game context. In particular, we uncovered differentiations based on player traits in the established link between need satisfaction and motivation.

An ecologically-valid setting has several advantages when investigating the moderating effects of personality types and player centric traits on the play experience: 1) The relation between need satisfaction and motivation is not investigated under experimental situations, which limits experienced autonomy because of an external source of motivation, e.g. financial compensation; 2) We do not have to extrapolate on how our findings might generalize to real-world in-game behavior because we have access to that data directly; and 3) In-game behavior is not influenced by time pressure, as is often introduced in experiment-based play sessions.

Our results also shed light on how differences in experience are reflected in different in-game behaviors. This is especially important in cases of moderation because we must consider motivation and traits in combination to understand player behavior, and cannot rely on the predictive ability of each construct in isolation.

Our results can give designers concrete insights on how to improve player experience for specific player personas, for instance which need factors are most important to satisfy for players with certain traits. In the long term, we envision a game platform that customizes the game experience for each player by knowing his or her traits. For example, if a player is a high achiever, then the game should foster a sense of relatedness, and this can be achieved by monitoring and triggering specific actions (e.g. social claims). However, if the player is not a high achiever, then there is no need to focus on satisfying relatedness, and the game may need to focus on satisfying other needs by considering a different trait. It is future work to determine how and when to adapt, but we have initiated this effort by building the knowledge of who to adapt for.

Although our findings are limited to Pot Farm, the approach is general and can be extended to other genres. Specific studies are needed in order to uncover how different games, e.g. a first-person shooter, might satisfy needs differently. Future work is also needed to find innovative ways to assess player-centric and personality traits without actually surveying players; e.g. personality predictions based on in-game behavior, or social network profile (i.e., [1,30]).

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