Modeling Individual Differences through Frequent Pattern Mining on Role-Playing Game Actions

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Abstract

There has been much work on player modeling using game behavioral data collected. Many of the previous research projects that targeted this goal used aggregate game statistics as features to develop behavior models using both statistical and machine learning techniques. While existing methods have already led to interesting findings, we suspect that aggregated features discard valuable information such as temporal or sequential patterns, which are important in deciphering information about decision-making, problem solving, or individual differences. Such sequential information is critical to analyze player behaviors especially in role-playing games (RPG) where players face ample choices, experience different contexts, behave freely with individual propensities but possibly end up with similar aggregated statistics (e.g., levels, time spent). Using an RPG with multiple affordances, we designed an experiment collecting granular in-game behaviors of 64 players. Using closed sequential pattern mining and logistic regression, we developed a model that uses gameplay action sequences to predict the real world characteristics, including gender, game play expertise and five personality traits (as defined by psychology). The results show that game expertise is a dominant factor that impacts in-game behaviors. The contributions of this paper are both the algorithms we developed combined with a validation procedure to determine the reliability and validity of the results, and the results themselves.

Introduction

Recently, digital games have increased in popularity as an entertainment medium as well as a medium for serious purposes, such as training, health or education (Goldman, 2010). To assist development, business and marketing teams, and to help assess the impact of such games (Yannakakis et al. 2013), researchers have started to investigate ways to model player behaviors (Drachen, Canossa, & Yannakakis, 2009; Mahlmann, Drachen, Togelius, Canossa, & Yannakakis, 2010; Pedersen, Togelius, & Yannakakis, 2009; Shaker, Yannakakis, & Togelius, 2011). Further, some of previous works have investigated individual differences and preferences through assessment of players' real world characteristics and its relation to their in-game players (Canossa et al. 2015; Erfani et al. 2010; Yee et al. 2011).

In order to quantify in-game actions, the player behavior modeling work mentioned above used aggregated statistics, such as time spent in certain game areas or sum of kills in one session, as features for predicting the relationships they investigated. This technique is rather limited, because only using aggregated features (e.g. level complete time, scores achieved, etc.) risks losing other critical information. For instance, completing the same actions in different orders to achieve a certain quest may be indicative of player preference. Furthermore, using these aggregated variables devoid from context is problematic. As psychology of personality suggests, the context within which an action is performed has an immense impact in interpreting the meaning of the action (Canossa et al., 2015; Mischel, 1968; Murray, 1938). Context is not just limited to the location within which an action takes place, but also the actions that precede and follow the action under examination. In this light, using full sequences of actions and a technique such as sequential mining can shed new light on an established practice.

In this paper, we use a combination of closed sequential pattern mining and logistic regression to develop a player model that can predict individual differences, including gender, game play expertise, or personality from player actions in an RPG. We use sequential pattern mining to extract action sequences that capture the order of in-game action execution. These action sequences are then used as input features to develop a machine learning model to predict real-world characteristics given behavior sequences. The real world characteristics of players we collect are: scores of the five personality traits described by the Five

Factor Model (Goldberg, 1993) as well as demographic data, e.g., gender and previous game experience in RPG games. Results should allow us to deduce unique signatures for specific personality or demographic given game actions. To validate our results, we used regularization, bootstrapping experiments and cross-validation.

Results showed that of all demographic and real-world data collected, former game experience is a dominant predictor of in-game behaviors. This is not surprising, as there are researchers who alluded to this (Erfani et al., 2010; Joorabchi & El-Nasr, 2011; Milam, Bartram, & El-Nasr, 2012). This paper confirms these results with evidence and empirical data. However, it also signals that using game data to understand real life characteristics is not straight forward, and game play expertise should be considered as a factor when analyzing and modeling player behaviors. In the future, we aim to use different techniques to minimize the influence of expertise or account for it when doing this analysis to develop a generic approach that can model individual differences.

The contributions of this paper is as follows: to the best of our knowledge, this is the first paper to apply sequential pattern mining algorithms on action sequences collected from RPGs for the purpose of understanding individual differences. The extracted patterns captured the order of individually executed actions, and thus provided richer information about game contexts and player historical decisions than aggregated features (e.g. level complete times and scores). In particular, the extracted patterns were informative for making further inferences of individual differences from the analysis results.

Previous Work

Given our interest in using game analytics to model players using action sequences as features, we will review related work within game analytics and player modeling communities. Since our approach was tested in an experiment looking at the connection between real-world variables, in particular demographics and personality, and in-game behaviors, we will also review research projects that investigated personality, player game expertise and in-game behaviors.

Analytics Methods for In-Game Behaviors

Sequential Pattern Mining Methods

In-game behaviors can be encoded as aggregated features (e.g. level completion time and scores), individual actions (such as establishing a building in RTS games) as well as sequences of actions. Sequences of actions reflect a series of decisions players make, which convey richer and complementary information as compared to aggregated features and individual actions. Frequent sequential patterns, or frequent patterns for short, are subsequences that appear often in a group of given sequences (Han, Kamber, & Pei, 2006). The support of a frequent pattern is the percentage of the given sequences that have frequent patterns within them. Common frequent pattern mining techniques aim to find frequent patterns with a given support. The biggest challenge of mining frequent patterns is that often too many subsequences with a given support are found, impeding further analysis. The number of frequent patterns usually increases substantially as the expected minimum support is tuned lower. In response, some sequential pattern mining algorithms, such as ClaSp (Gomariz, Campos, Marín, & Goethals, 2013), were designed to seek closed frequent sequential patterns, i.e., those containing no super sequence of the same support.

Game researchers have applied sequential pattern mining algorithms but mostly within the context of understanding and modeling strategies in Real Time Strategy (RTS) games. For example, Low-Kam et al. (2013) designed an algorithm to discover statistically significant, unexpected sequential patterns. Their algorithm was tested on a StarCraft (Blizzard Entertainment, 2010) building sequence dataset, which successfully highlighted an unusual strategy that was later identified by StarCraft experts. Bosc et al. (2013) used sequential pattern mining algorithms to analyze strategies that RTS players adopt to capitalize on detected weaknesses of opponents. In addition, Shaker et al. (2011) used sequential pattern mining to extract features that characterize level content in Super Mario Bros (Nintendo, 2004) in order to predict player self-reported engagement preferences. Martínez and Yannakakis (2011) mined frequent patterns from multimodal data (i.e., events of performance, navigation and physiology during gameplay). They then used them to predict self-reported affective state: anxiety, challenge, excitement, frustration, fun or relaxation.

While the work done on using sequential pattern mining with RTS has been geared towards finding popular or dominant strategies or understanding player strategies, and the work by Shaker et al. was geared towards procedural content generation, none of the previous work aimed to understand the impact of individual differences on game behavior. To this end, we opted to investigate action patterns from design spaces that are open and afford diverse action sets. Thus, we focus on RPGs. While the methods and techniques developed by previous work can be similar, we hypothesize that investigating an RPG domain will consider different feature sets. This paper aims to develop the first step towards this goal.

Machine Learning Methods

With rapid development of machine learning techniques in recent years, an increasing number of studies have applied machine learning methods to games to predict player behaviors, most of which are commercial games with huge data of player in-game behaviors to train accurate machine learning models. For example, Mahlmann et al. (2010) trained various machine learning algorithms (Logistic regression, MLP/Backpropagation, Decision tree, etc.) to predict the last level a player will complete. They used a large-scale set of in-game behaviors data from Tomb Raider: Underworld (Eidos Interactive 2008). Shaker et al. (2013) used gameplay aggregated statistics, to train a neu-

	Expertise	Gender	O	C	E	A	N
0	29	34	12	9	13	11	9
1	35	30	11	8	10	10	9

Table 1: Statistics of the 64 subjects. O, C, E, A, N represent Openness, Conscientiousness, Extroversion, Agreeableness and Neuroticism respectively from the NEO-PI-R. For the traits, 0 indicates a low score and 1 a high score. Note numbers of subjects with intermediate trait scores are not reported.

ral network model (Yannakakis, Maragoudakis, and Hallam 2009) to predict player self-reported emotional states in a First-Person Shooter game.

While there are much works in this area, only very few used machine learning to understand the impact of individual differences on virtual behaviors. The reason for the lack of research in this area is that there are many empirical limitations to collecting large data sets both of in-game data and real world information (e.g. personality scores and game expertise). In the next section we discuss the few works that investigated individual differences.

In-Game Behaviors and Individual Differences

There have been numerous attempts to profile in-game behaviors in relation to individual differences (Bartle 1996; Bateman and Boon 2005; Canossa, Martinez, and Togelius 2013; Joorabchi and El-Nasr 2011; Van Lankveld, Schreurs, and Spronck 2009; Van Lankveld 2013; Van Lankveld et al. 2011; Tekofsky et al. 2013; Yee et al. 2011). For example, Canossa et al. (Canossa et al., 2013) investigated the psychological motivations behind game behaviors in Minecraft (Mojang, 2011) using Reiss's individual differences model (Reiss, 2008). Specifically, they asked 90 players to take Reiss's test and collected 546 in-game behaviors. Results show that motivational factors, namely: honor, romance, independence and acceptance, have significant correlations with game behaviors. Yee et al. (2011) correlated gameplay behavior with the five-factor personality model (FFM) (Costa & McCrae, 1992) for the Massively Multiplayer Game, World of Warcraft (Blizzard Entertainment, 2004). They found significant correlations for each of the five traits although no coefficients exceeded ±0.17. In recent work, Canossa et al. (2015) examined the relationship between FFM personality data (Costa & McCrae, 1992) and in-game behaviors in different game contexts. They found that the correlations are much stronger when contexts and facets are used for the analysis.

In addition to personality, there has been some work presenting clear evidence of the impact of player expertise as a factor influencing game play behavior. For example, Milam et al. (2012) reported that game expertise has a significant effect on critical metrics of a railed-shooter game, such as accuracy and level time. Erfani et al. (2010) conducted experiments investigating the impact of age, gender and gaming expertise on game play performance among 60 kids. They only found positive correlation between gaming expertise and performance variables. These works suggest that game play expertise is an important variable to consider when investigating individual differences.

Design and Methodology

The Data

We used data collected from an experiment conducted with 71 subjects (age: 20.56 ± 2.2). Data collected from this experiment were: in-game behaviors (discussed below), the Big Five trait scores of players defined in NEO-PI-R (Costa & McCrae, 1992), player game expertise (we used a questionnaire developed by Erfani et al. (2010)) and gender.

Real-life Characteristic Data

A survey was used to collect:

- Gender: 0 is female, 1 is male.
- Player expertise: 1 (high expertise)/0 (low expertise), where high expertise was defined as playing RPGs at least weekly, and selecting RPG as their favorite genre.
- Personality: using the NEO-PI-R (Costa & McCrae, 1992), we gathered scores for each participant on five traits: Extroversion, Conscientiousness, Agreeableness, Neuroticism, Openness to experience). An additional procedure of trait binarization was done. A player was considered to have a "high" score in one trait if the score was one standard deviation higher than the mean of all players. Similarly, a "low" score was one standard deviation lower than the mean. Note that the binarization step filters out the players with intermediate scores when we investigate certain traits. Although this method reduces the number of data points available, our justification is that the scale of personality scores may only be accurate to identify strongly expressed traits which are more likely to be reflected in gameplay. Moreover the normality of data was checked to hold in our preliminary analysis, which permits the validity of the binarization procedure. In the end, there were 64 subjects contributing valid data. The breakdown of the dataset can be viewed in Table 1.

In-game Data

The in-game behavior data was collected using a game scenario designed using the Fallout: New Vegas engine (Bethesda Softworks, 2010). The scenario contained standard RPG affordances: exploration of different areas, such as the *Intro House*, *Mine* or *Outside*, obtaining weapons and other objects, conversing with non-player characters (NPCs) though dialog trees, performing quests or engaging in combat. A "main quest was provided as the primary scenario objective, but players were not compelled to pursue it. The scenario contained 60 minutes of gameplay.

The game was instrumented so that every action executed by a player was saved canonically to a local file indexed by subject identification. A valid action record included its

Frequent patterns	Support	Explanation
1→2→24→30→31	59%	The player starts at Intro House (1), followed by starting a mandatory conversation (2), followed by talking to Mr. Walker (an NPC) about his gratefulness and asking about bikers (24), followed by telling Mr. Walker that "I'll be on my way now" (30), then going to the *Outside* (31).
1→2→3→5→5→31→31	67%	The player starts at Intro House (1), followed by starting a mandatory conversation (2), followed by asking Tracy (An NPC) "Where am I?" (3), followed by interacting with objects in Wardrobe two times (5), and followed by being to the Outside for at least two times (31)

Table 2: Two examples of extracted closed sequential patterns and their explanation. A frequent pattern consists of action IDs with arrows in between indicating the order they happened.

action type (mandatory field) and optional information, such as the location where the action took place. For instance, "Player killed rats, Intro House" is an action entry recorded when a player killed rats at a location encoded Intro House by developers. There were a total of 520 distinct actions recorded in the game.

Analysis Method

In order to capture the order of action execution, we apply Clasp (Gomariz et al., 2013) to mine closed sequential patterns with over 40% support in all action sequences using the open source library SPMF (Fournier-Viger et al., 2014). Then, a filter process was performed to prune frequent patterns with more than 70% support. The justification for choosing only 40%-70% support closed frequent patterns is that subsequences played by too few players or by the majority of players would not help discriminate between different groups, and thus can be discarded. Two samples of extracted closed frequent patterns and their explanation are shown in Table 2. In total, 5304 closed sequential patterns were extracted. Finally, whether a player acts according to the exact order of a closed pattern is represented as a binary feature for later data analysis.

Our goal was to predict real world characteristics of players based on execution of all the extracted closed sequential patterns. Although there are other more complicated classification algorithms such as random forests and neural networks, we used Logistic regression with L_1 regularization as a predictor model. This was done, because: (1) Logistic Regression works well with categorical values through modeling the likelihood probabilities of categorical classes and choosing the category with the largest likelihood probability as prediction result. Since our data is binary (i.e., high/low scores of traits, male/female and gamer/non-gamer), it was a natural fit. (2) Result interpretability is important to uncover the connection between behaviors and individual differences. A trained logistic regression model associates each predictor variable with a weight. The absolute value of a weight is the importance of the variable and the sign of the weight indicates the direction of the impact, i.e., positive or negative. (3) Ng (2004) proved that logistic regression with L_1 regularization can be effective in feature selection because the model can learn well even with an asymptotically exponential number of irrelevant features relative to the size of training data. In our case, the number of subjects is far less than the number of closed patterns, large numbers of which may not be related to any real world characteristics. Therefore, effective feature selection methods, such as Logistic Regression with L_1 regularization, are needed. Note that if there exists multiple correlated features, which simultaneously help prediction, logistic regression with L_1 regularization tends to only assign the weight of one feature among them and keep the others zero.

Using Logistic regression, the procedure was as follows. For each variable to be predicted (e.g., gender, personality trait or game expertise), a logistic regression model with all features included was provided initially. L_1 regularization, whose impact in the logistic regression model is controlled by a parameter λ, was added in the form of constraints to the model during training. Since we didn't know the preferable value of λ in advance, a grid search on λ was performed. In other words, there were multiple logistic regression models with different strengths of L_1 regularization to be trained for each relationship. To validate the trained models, we used leave-one-out cross validation (Lachenbruch & Mickey, 1968) for the models corresponding to each value of λ in the grid search. We report any relationship with low misclassification error in the cross validation. Predictor variables were always standardized before a model starts training.

Results and Validation

The lowest misclassification errors with proper λ were achieved by: 25% Game Expertise, 26.1% Extroversion, 27.8% Neuroticism, 29.4% Conscientiousness, 37.5% Gender, 47.8% Openness and 52.4% Agreeableness. At first glance, the models for gender, openness and agreeableness do slightly better or no better than random guesses based on majority class labels (as can be deduced from Table 1). The easiest real world characteristic to predict is High/Low game expertise with a 25% misclassification error, i.e., one out of four players will be predicted incorrectly.

After obtaining these results, a bootstrapping test was performed to assess the reliability of the models with a misclassification error of 30% or below. For the bootstrap, the same procedure of training logistic regression (with grid search on λ and leave-one-out cross validation) was applied on the data, except that the players' real-world characteristics were resampled with replacement. The

Weight	Pattern / Explanation
-0.4	1→2→7→22→23→26→31→32→33 The negative weight indicates that the pattern, if present in a player's action sequence, is more likely executed by a low expertise player. We found that 22 out of 29 low expertise players had this pattern while only 16 out of 35 high expertise players had it. The sequence features asking Mr. Walker "Where am I exactly?" (22, 23) and later interacting with David Johnson, who is another NPC providing information at *Outside* (33). We speculate the reason for fewer high expertise players behaved in this pattern that they prefer exploring the game world by themselves rather than asking such template question to an NPC that are uncommon in real commercial games. Action 1, 2, 7, 26, 31 and 32 are common behaviors that almost every player would have (e.g. accepting the first mandatory quest). Therefore they don't help discern this pattern.
0.4	1→2→7→8→10→8→31→32→178→179→180 Only 6 out of 29 low expertise players had this pattern in their action sequences while 25 out of 35 high expertise players had it. This sequence is featured by multiple interactions with Mr. Walker (8, 10), arriving at the *Mine* and initiating a quest dialogue there (178, 179, 180). This result again confirms the explorative tendency of high expertise players because *Mine* is an inconspicuous location far away from several main buildings of the game and players can't know any information about it from other locations except they happen to arrive *Mine* themselves.
-0.18	1→2→7→26→28→31 Another closed pattern which is more favored by low expertise players, as shown by the negative weight. This sequence features requesting that Mr. Walker tell the player more about the town (28), similar to the first sequence above. The same reasoning could also be applied here.

Table 3: Selected closed patterns which help predict game expertise. The column "Weight" denotes their associated weights in the logistic regression model.

bootstrap simulation run 1,000 times and the lowest classification error in the grid search for each run was collected to form a distribution. The misclassification errors of the models obtained for extroversion, neuroticism and conscientiousness lay within one standard deviation of the mean error. This indicates that it is very likely that our models can achieve a 25%~30% misclassification error by chance. The only exception was the model for game expertise, whose misclassification error was around two standard deviations lower than the mean error.

We thus reject the models for conscientiousness, extroversion and neuroticism. Interpreting the results qualitatively, we found that the frequent patterns associating with the non-zero weights make sense to researchers who are familiar with the test game. The interpretation of three such patterns is listed as examples in Table 3.

These results confirm findings in (Erfani et al., 2010; Joorabchi & El-Nasr, 2011; Milam, Bartram, & El-Nasr, 2012) about the evident impact of game expertise on virtual world behaviors. It also suggests researchers to consider the impact of game expertise when they investigate individual differences using digital games.

Conclusion

The method and results show the feasibility of using frequent pattern mining algorithms to extract behavioral features to develop predictive models that can be meaningful to understand individual differences. Our results allude to the very strong effect of game expertise on game behavior.

The analysis and validation methods used constitute a contribution to the field. Most previous work on modeling of individual differences use aggregated player actions statistics. As shown, we can deduce better results and more insight through sequence pattern mining. Although frequent pattern mining algorithms may result in a large number of frequent patterns as features, we showed that a properly selected predictive model with regularization, cross validation and bootstrap can help confirm the validity of results.

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References

Bartle, R. 1996. Hearts, clubs, diamonds, spades: Players who suit MUDs. *Journal of MUD Research*, *1*(1), 19.

Bateman, C., and Boon, R. 2005. *21st Century Game Design (Game Development Series)*. Charles River Media, Inc.

Bosc, G.; Kaytoue, M.; Raïssi, C.; and Boulicaut, J. 2013. Strategic Pattern Discovery in RTS-games for E-Sport with Sequential Pattern Mining.

Canossa, A.; Badler, J.; Seif El-Nasr, M.; Tignor, S.; and Colvin, R. 2015. In Your Face(t) Impact of Personality and Context on Gameplay Behavior. In *Foundations of Digital Games*.

Canossa, A.; Martinez, J. B.; and Togelius, J. 2013. Give me a reason to dig Minecraft and psychology of motivation. In *2013 IEEE Conference on Computational Inteligence in Games (CIG)* (pp. 1–8). IEEE.

Costa, P. T., and McCrae, R. R. 1992. *NEO Personality Inventory Revised (NEO PI-R)*. Psychological Assessment Resources.

Drachen, A.; Canossa, A.; and Yannakakis, G. N. 2009. Player modeling using self-organization in Tomb Raider: Underworld. In *2009 IEEE Symposium on Computational Intelligence and Games* (pp. 1–8). IEEE.

Erfani, M.; Seif El-Nasr, M.; Milam, D.; Aghabeigi, B.; Lameman, B. A.; Riecke, B. E.; Maygoli, H.; and Mah, S. 2010. The effect of age, gender, and previous gaming experience on game play performance. In *Human-computer interaction* (pp. 293–296). Springer.

Fournier-Viger, P.; Gomariz, A.; Gueniche, T.; Soltani, A.; Wu, C.-W.; and Tseng, V. 2014. SPMF: a Java Open-Source Pattern Mining Library. *Journal of Machine Learning Research*.

Goldman, T. 2010. Videogame Industry Worth Over $100 Billion Worldwide.

Gomariz, A.; Campos, M.; Marín, R.; and Goethals, B. 2013. Clasp: An efficient algorithm for mining frequent closed sequences. In *Advances in Knowledge Discovery and Data Mining* (pp. 50–61). Springer.

Goldberg, L. R. 1993. The structure of phenotypic personality traits. *American Psychologist*. 48(1), 26.

Joorabchi, M. E., and Seif El-Nasr, M. 2011. Measuring the impact of knowledge gained from playing FPS and RPG games on gameplay performance. In *Entertainment Computing--ICEC 2011* (pp. 300–306). Springer.

Lachenbruch, P. A., and Mickey, M. R. 1968. Estimation of Error Rates in Discriminant Analysis. *Technometrics*, *10*, 1–11.

Low-Kam, C.; Raissi, C.; Kaytoue, M.; and Pei, J. 2013. Mining Statistically Significant Sequential Patterns. In *2013 IEEE 13th International Conference on Data Mining* (pp. 488–497). IEEE.

Mahlmann, T.; Drachen, A.; Togelius, J.; Canossa, A.; and Yannakakis, G. N. 2010. Predicting player behavior in Tomb Raider: Underworld. In *Proceedings of the 2010 IEEE Conference on Computational Intelligence and Games* (pp. 178–185). IEEE.

Martínez, H. P., and Yannakakis, G. N. 2011. Mining multimodal sequential patterns. In *Proceedings of the 13th international conference on multimodal interfaces - ICMI '11* (p. 3). New York, New York, USA: ACM Press.

Milam, D.; Bartram, L.; and Seif El-Nasr, M. 2012. *Investigation of Expertise and Visual Balance in a Railed-Shooter game*.

Mischel, W. 1968. *Personality and Assessment*. New York: Psychology Press.

Murray, H. A. 1938. *Explorations in personality.* New York: Oxford University Press.

Ng, A. Y. 2004. Feature selection, L 1 vs. L 2 regularization, and rotational invariance. In *Twenty-first international conference on Machine learning - ICML '04* (p. 78). New York, New York, USA: ACM Press.

Pedersen, C.; Togelius, J.; and Yannakakis, G. N. 2009. Modeling player experience in Super Mario Bros. In *2009 IEEE Symposium on Computational Intelligence and Games* (pp. 132–139). IEEE.

Reiss, S. 2008. *The Normal Personality: A New Way of Thinking about People*.

Shaker, N.; Shaker, M.; Abuabdallah, I.; Zonjy, M.; and Sarhan, M. H. 2013. A Quantitative Approach for Modeling and Personalizing Player Experience in First-Person Shooter Games. In *2013 Conference on User Modeling, Adaptation and Persolization*.

Shaker, N.; Yannakakis, G. N.; and Togelius, J. 2011. Feature analysis for modeling game content quality. In *2011 IEEE Conference on Computational Intelligence and Games (CIG'11)* (pp. 126–133). IEEE.

Tekofsky, S.; Spronck, P.; Plaat, A.; den Herik, J.; and Broersen, J. 2013. Psyops: Personality assessment through gaming behavior. In *BNAIC 2013: Proceedings of the 25th Benelux Conference on Artificial Intelligence, Delft, The Netherlands, November 7-8, 2013*.

Van Lankveld, G. 2013. *Quantifying Individual Player Differences*.

Van Lankveld, G.; Schreurs, S.; and Spronck, P. 2009. Psychologically Verified Player Modelling. In *GAMEON* (pp. 12–19).

Van Lankveld, G.; Schreurs, S.; Spronck, P.; and Van Den Herik, J. 2011. Extraversion in games. In *Computers and Games* (pp. 263–275). Springer.

Yannakakis, G. N.; Maragoudakis, M.; and Hallam, J. 2009. Preference Learning for Cognitive Modeling: A Case Study on Entertainment Preferences. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *39*(6), 1165–1175.

Yannakakis, G.; Spronck, P.; Loiacono, D.; and André, E. 2013. Player Modeling. In *Artificial and Computational Intelligence in Games* (pp. 45–59).

Yee, N.; Ducheneaut, N.; Nelson, L.; and Likarish, P. 2011. Introverted elves & conscientious gnomes: the expression of personality in world of warcraft. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 753–762).