A statistical analysis of Steam user profiles towards personalized gamification

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Abstract. Gamification is widely used as motivational design towards enhancing the engagement and performance of its users. Many commonly adopted game design elements have been verified to be effective in various domains. However, the designs of such elements in the majority of the target systems are similar. Due to inevitable differences between users, gamification systems can perform more effectively when users are provided with differently and personally designed features according to their preferences. Many studies have suggested such requirements towards personalizing gamified systems based on the users' preferences, with categorizing gamification users and identifying their preferences as the initial step. This study proposes a preliminary analysis of the factors that categorize user preference in a game community, based on the user profiles data of the Steam platform. It shall not only facilitate understanding of players' preferences in a game community but also lay the groundwork for the potential personalized gamification design.

Keywords: Gamification · Exploratory Factor Analysis · Steam · User Profile · Preference · Personalized Gamification.

1 Introduction

Gamification, commonly defined as the use of game design elements for non-game contexts [12], has been widely adopted as motivational design to support users motivation enhancement and performance improvement. Many game design elements, e.g., badges/achievements, points, leaderboard, progress, story, etc., have been adopted in various service domains and proven effective in many studies [14]. However, the majority of the gamification systems provide very limited alteration towards different users but adopt the one-size-for-all design approach instead [32]. Such rigid gameful designs are to a certain extent ineffective in persuading the users into positive behaviors. Many studies have shown that different users are likely to be motivated by different game elements and persuasive strategies [31, 32, 40]. Therefore, it is critical to understand different users' preferences when providing them the personalized gameful experiences.

The studies on the users' types and preferences regarding gamification systems are based on the similar studies on game players. A seminal study on the player types for multi-user dungeon (MUD) games is Bartle's player typology [2]. Meanwhile, a number of studies also contribute to extending the user typology framework by focusing on psychographic and behavioral aspects [15]. Even though the direct connection is not addressed, such studies on player typology do facilitate the understanding of users preference of play style and their motivations of playing [15]. On the other hand, a gamification-specific user typology framework is developed by Marczewski [26], who proposes six gamification user types based on intrinsic or extrinsic motivational affordances [36] and their different degrees for the users. Furthermore, based on this particular framework, a 24-item survey response scale is presented to score users' preferences regarding the six different types of motivation toward a gameful system, which can therefore identify a users type and describe his/her preferences [42].

Despite the uniform well-defined player types and gamification user types, such a 'clear-cut' categorization approach can be questioned as a player may not belong to a certain type strictly [15, 21]. In addition, limitations of using survey data towards such categorization have also been recognized [42]. In this study, we focus on users of the Steam platform and their community-related behaviors presented on their profile pages. The users' Steam profiles provide various information, including the games they have, the game achievements, item trading, friends, groups, reviews, screenshots, profile customization options, and so on. The objective nature and large volume of such data shall has the potential to yield enhanced characterizations of users and their diferences. Herein, based on factor analysis of large user profile data, we identify the factors that characterize the differences between Steam users. Instead of a strict categorization of players, the study aims to answer what are the factors that distinguish Steam users from one another and determine their preferences, as well as how such distinguishing factors can be applied to facilitate personalized gamification design.

The paper is organized as follows. Section 2 introduces previous studies on game players and gamification user typologies and on analysis of the Steam platform and user data. Section 3 introduces our data collection and analysis methods, Sections 4 and 5 present results and discussion Section 6 concludes.

2 Related Work

2.1 Player Types and Gamification User Types

The aim of segmentation in marketing is to identify different customer groups so that they are served with products and services that match their unique needs. Studies on player types also serve this purpose. The majority of the prevailingly cited studies focus on the player segmentation in terms of the behavioral and psychographic attributes instead of geographic or demographic ones [15]; our focus is similar, since our Steam profiles did not contain demographic/geographic attributes and we focused on the available profile information reflecting player behavior. When available, our modeling principle could accommodate demographic/geographic attributes as covariates.

Bartle's seminal player typology — Achiever, Explorer, Socializer and Killer — is based on the things people enjoy about MUD in either an action or interaction dimension towards either players or the game world [2]. It is also criticized for being dichotomous and too simplifying, as well as focusing on only one game genre instead of a broad range [3, 15, 42]. Extending Bartle's typology model, many studies have proposed similar typology models for online game players with specialized focuses [43, 45]. Many other studies present different ways of categorizing players based on their various motivation and behaviors when not fixating on online games [21, 39]. Such player typology models provide ways to detect the difference in players and their preference regarding motivations and behaviors in general. On the other hand, many studies also focus more specifically on players' preferences regarding game design elements [11, 19].

The studies on gamification user types also adapt the results from the player typology studies. Such studies are mostly supported by the research on behavior motivations and personalities [29,36]. Regarding the user typology in the gamification domain, Marczewskis gamification user type model is the most cited work [26]. Motivated by the intrinsic and extrinsic motivational factors of the users, which is defined by the Self Determination Theory (SDT) [35], Marczewski categorizes the users of gamification services into six types, including socializers, achievers, philanthropists, free spirits, players, and disrupters. Other studies also attempt to provide adapted typology frameworks regarding specific domains [1,44]. Meanwhile, adapting Marczewski's gamification user types model, Tondello et al. present and validate a standard scale to determine users' preference towards gamification systems regarding different motivation types [42]. Based on that, their subsequent works contribute to suggesting gameful design elements regarding user preferences, personalizing persuasive strategies, and creating a recommender system model for personalized gamification [32, 40, 41]. However, mentioned as their limitation, the data are self-reporting and subject heavily to participants' personal understanding of survey statements and preferences towards diverse game elements. Thus, relevant objective data with a larger sample volume can address such limitation and can also yield alternative results.

2.2 The Steam Platform and Users

Steam, a popular digital game distribution platforms, has drawn attention from the academia. Becker et al. analyze the role of games and groups in the Steam community and present the evolution of its network over time [5]. O'Neill et al. also investigate the Steam community but focus on the gamers' behaviors, in terms of their social connectivity, playtime, game ownership, genre affinity, and monetary expenditure [30], whereas Blackburn et al. focus more specifically on the cheating behavior [7]. Many other studies also investigate the various perspectives of players' behaviors on the Steam platform. For example, Sifa et al. investigate the players' engagement and cross-game behavior by analyzing their different playtime frequency distributions [37,38]. Baumann et al. focus on "hardcore" gamers' behavioral categories based on their Steam profiles [4]. Lim and Harrell examine players' social identity and the relation between their profile maintaining behaviors and their social network size [22]. Meanwhile, other scholars also study the other perspectives of Steam, such as, recommender systems for its content [6], early access mechanism [24], game updating strategies [23], game reviews [25], and so on. However, research on characterizing players based on their Steam profile data towards analyzing players' preference to different game design elements is still limited.

3 Method

3.1 Data Collection

A web crawler based on the Beautiful Soup Python module was created to collect data from public user profiles. The data collection proceeded in a "snowball" manner. The crawler started from one user's Steam profile URL which was selected at random from the top 10 Steam user leaderboard, and crawled the list of the user's friends profile URL. Iteratively, the list of users was grown via crawling the friends of each of the existing users on the list and appending the results to the end of the list. Although guaranteeing an unbiased sample from such a huge base is difficult and our gathered dataset is necessarily small, it can still achieve a good representativity. Duplicated profile URLs, as well as private ones from which no valid data can be obtained, were eliminated. To reduce crawling time while achieving reasonable coverage, only profile URLs were crawled, and from the initial data pool of 2561387 unique user profile URLs, we collected the profile information on a random subset of the URLs which includes 60267 users. The crawled features include *Levels*, *Showcases*, *Badges*, *Number of Games*, *Screenshots*, *Workshop Items*, *Videos*, *Reviews*, *Guides*, *Artworks*, *Groups*, *Friends*, *Items Owned*, *Trades Made*, *Market Transactions*, *Achievements*, *Perfect Games*, *Game Completion Rate*, and four binary *profile customization* related variables: *Avatar*, *Status*, *Background*, and *Favorite Badge* customization (customized or not). To summarize the binary variables per user, we define an aggregate value called *Profile Customization* whose value is the percent of 'customized' values: for example, if a particular user customized three of the four items mentioned above, his/her *Profile Customization* score will be assigned as 0.75. In addition, each user's active time span was also collected based on the time when the user last logged off and the time when the user created the account, using the SteamAPI. To take the user activity into account, we further computed the duration the profile had existed using the above-mentioned information and utilized it to normalize the profile variables, by simply dividing each variable by the profile duration.

3.2 Exploratory Factor Analysis

To uncover the underlying structures of the Steam user profiles, an exploratory factor analysis (EFA, [13]) is conducted. It enables us to reduce the complexity of the data, explain the observations with a smaller set of latent factors and discover the relations between variables. Unlike clustering which discovers groups of players, EFA discovers underlying axes characterizing players and their differences. In game culture studies, EFA has been widely used especially in studies related to user/player types and user motivations (e.g. [42, 43]). Extracted EFA factors can also be a basis for analysis such as clustering (player segmentation) or prediction in follow-up work; we focus on discovering underlying axes of variation in Steam user profiles through EFA and their applications in gamification.

One common issue in EFA is how to decide the number of factors. In this paper, the parallel analysis (PA) introduced by Horn [18] is adopted to solve the problem. It has been widely used and has given good results in recent research works (e.g. [33, 34]). Several comparative studies (e.g. [8,46]) have shown that it is an effective way to determine the number of factors.

Table 1. Result of Parallel Analysis

Factor	Observed Eigenvalue	Simulated Eigenvalue
1	3.104	1.031
2	2.744	1.025
3	1.650	1.021
4	1.382	1.018
5	1.167	1.015
6	1.130	1.011
7	1.073	1.008
8	1.027	1.006
9	0.916	1.003

In PA, the Monte Carlo simulation technique is employed to simulate random samples consisting of uncorrelated variables that *parallel* the number of samples and variables in the observed data. From each such simulation, eigenvalues of the correlation matrix of the simulated data are extracted, and the eigenvalues are, as suggested in the original paper [18], averaged across several simulations. The eigenvalues extracted from the correlation matrix of the observed data, ordered by magnitude, are then compared to the average simulated eigenvalues, also ordered by magnitude. The decision criteria is that the factors with observed eigenvalues higher than the corresponding simulated eigenvalues are considered significant. Hereby, we conduct the parallel analysis task with 5000 simulations to determine the number of factors.

To simplify interpretation of the factor analysis result, the *varimax* rotation technique [20] which maximizes the variance of the each factor loading is employed. Results with an alternative rotation approach *promax* [17] were similar.

4 Result

4.1 Factor Analysis

The result of the parallel analysis is shown in Table 1. Based on the mentioned criteria, the turning point can be found easily by examining the differences between observed eigenvalues and simulated eigenvalues. Since the simulated eigenvalue becomes greater than the observed eigenvalue in the 9th factor (1.003 and 0.916 respectively), the first 8 factors are retained. The corresponding factor loadings can be found in Table 2. A cross-loading of the variable Profile.Customization was found on Factor 1 and 7, we further computed the Cronbach's alpha [9] on those two factors to evaluate their internal consistency and the values are found acceptable (0.87 and 0.71 respectively).

4.2 Factors Interpretation

Based on the result of EFA, we interpret each of the eight factors and summarize each of the unique preference attributes of Steam users.

Table 2. Loadings of the Extracted Factors

Variable	Factor 1	2	3	4	5	6	7	8
Level	**0.641**	-0.005	0.004	-0.002	0.008	-0.013	-0.263	0.002
Showcases	0.026	0.107	0.065	**0.828**	0.162	0.180	0.028	0.067
Badges	**0.954**	0.033	0.004	0.010	0.006	0.043	0.016	0.004
Games	0.019	**0.511**	0.020	0.016	0.108	0.365	0.030	0.088
Screenshots	-0.000	0.118	0.332	0.046	0.344	0.039	0.022	**0.490**
Workshop.Items	0.007	-0.045	0.042	0.127	**0.789**	-0.027	0.003	-0.082
Videos	0.002	-0.030	-0.066	0.046	-0.074	-0.022	-0.003	**0.901**
Reviews	0.002	0.232	0.039	0.044	**0.769**	0.039	0.018	0.113
Guides	0.002	0.024	**0.879**	-0.031	-0.090	-0.003	-0.001	-0.002
Artwork	0.004	-0.010	**0.836**	0.101	0.192	0.006	0.018	0.030
Groups	0.078	0.017	0.020	0.031	0.026	0.008	**0.951**	0.009
Friends	**0.947**	0.002	0.004	0.043	0.007	0.014	0.202	0.001
Items.Owned	0.004	0.048	0.005	0.049	-0.004	**0.733**	0.006	-0.022
Trades.Made	-0.003	-0.142	-0.002	0.281	-0.063	**0.551**	0.003	-0.061
Market.Transactions	0.017	0.116	0.001	-0.063	0.044	**0.645**	-0.007	0.049
Achievements	0.005	**0.865**	0.014	0.125	0.014	-0.010	-0.001	-0.011
Perfect.Games	0.003	**0.847**	0.006	0.210	0.105	-0.045	-0.002	-0.017
Game.Completion.Rate	0.008	0.274	0.013	**0.852**	0.054	-0.004	0.003	0.021
Profile.Customization	**0.808**	-0.007	-0.008	-0.019	-0.015	-0.016	**0.553**	-0.007

Factor 1: Elite (Level, Badge, Friends, and Profile Customization) Factor 1 indicates the users' tendency to become the elite of the Steam community. The *elite* users focus on their social comparison advantages over the others by enhancing their quantifiable social scores, such as, levels, badges, and friends numbers. According to Steam's unique mechanism, the users can upgrade their levels and earn more badges without the requirements of exerting more effort in actual gameplay. Therefore, the elite users tend to value their social achievement more than experiences in gameplay. In addition, they also prefer profile customization in order to present their unique social identity.

Factor 2: Achiever (Games, Achievement, and Perfect Games) Users' tendency in Factor 2 indicates their preference towards mastering the games. They focus on completing games thoroughly and obtaining as many in-game achievements as possible. They also tend to enlarge their game collection whenever possible. Compared to the *elite* users, the *achiever* users prefer to put their effort in games and less in social.

Factor 3: Provider (Guides and Artworks) Users with high attribute in Factor 3 love to provide facilitation to the others with gameplay guides and self-created unique game-related arts. Different from *elite* and *achiever* users who focus on their social presence or achievement, the *provider* users tend to be more altruistic and care about other users and their game playing.

Factor 4: Completer (Showcases and Game Completion Rate) Similar to the *achiever* users, the *completer* users also focus on gameplay but less on achievements. They prefer to finish the games that they start but have less intention of pursuing the full achievement by investing extra amount of hours. Meanwhile, they like to show their possessions, e.g., showcases, as much as possible, but put less effort on organizing compared with the *elite* users.

Factor 5: Improver (Workshop Items and Reviews) Users with high value on Factor 5 focus on game improvement. They make efforts to add unique experiences to games via workshop items and reviews. These encourage developers to improve the games and publish better games in the future. Similar to *provider* users, they are also altruistic but focus more on game quality.

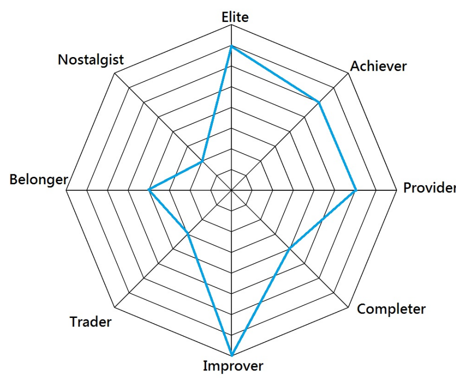

Fig. 1. An Example of User Preference Attributes Radar Chart

Factor 6: Trader (Item Owned, Trades Made, and Market Transaction) The *trader* users do not pay much attention to either games or social, but to buying and selling game related virtual items instead. According to Steam's mechanism, users neither have to own or play games to obtain items nor have to become friends with others or join groups to make trades. Thus, *trader* users tend to make the community a business playground, buying low and selling high.

Factor 7: Belonger (Groups and Profile Customization) Similar to the *elite* users, the *belonger* users also tend to focus more on social interaction than gameplay, when the difference is that the belonger users prefer the feeling of relatedness and belonging, rather than social comparison. Belonging to social groups is always their first priority. Having a proper customized profile is thus also necessary to fit them in the groups.

Factor 8: Nostalgist (Screenshots and Videos) Users with high *nostalgist* attribute have the tendency of restoring their gameplay memories by taking screenshots and recording videos. They also share their gameplay memories with others in the activity timeline, so that other players can enjoy the unique scenes and compare to their own gameplay too. Meanwhile, the ”thumbs up” and appreciation from the others is their reward.

It is worth noting that the eight factors aim to explore the various attributes of Steam users instead of arbitrarily categorizing each user into a single type. Generally, each individual user shall contain certain scores in all given attributes while the attribute value distribution of different users shall differ. Meanwhile, each user may also contain high or low score in multiple attributes simultaneously. By reducing the variable dimensions to one for each attribute and normalizing the value, each individual user shall have a radar chart illustrating his/her salient attributes. Fig. 1 shows an example of a user who possesses a salient attribute of *improver* and is creative with workshop items and also loves to contribute in improving games by giving reviews. Meanwhile, this particular user also possesses relevantly salient attributes of *elite*, *achiever*, and *provider*. It indicates that the user also favors gaining levels, badges, and achievements, and providing guides and artworks to the community.

Table 3. An Example Mapping between Preference Attributes and Motivation Types

Attributes	Steam Variables	Motivation Types [10, 36]	Gameful Elements [40]
Elite	Level	Mastery	Progression
	Badges	Mastery	Incentive
	Friends	Relatedness	Socialization
	Profile Customization	Autonomy	Customization
Achiever	Games	Mastery	Progression
	Achievements	Mastery	Incentive
	Perfect Games	Mastery	Incentive
Provider	Guides	Mastery, Purpose	Altruism
	Artwork	Autonomy	Altruism
Completer	Showcases	Autonomy, Mastery	Customization
	Game Completion Rate	Mastery	Progression
Improver	Workshop Items	Autonomy, Purpose	Altruism
	Reviews	Autonomy, Purpose	Altruism
Trader	Items Owned	Mastery	Incentive
	Trades Made	Relatedness	Socialization
	Market Transactions	Relatedness	Socialization
Belonger	Groups	Relatedness	Socialization
	Profile Customization	Autonomy	Customization
Nostalgist	Screenshots	Autonomy, Relatedness	Socialization
	Videos	Autonomy, Relatedness	Socialization

To apply such a preference framework in gamification design, based on the variables each attribute is related to, we could find connections between attributes and the established intrinsic motivation types or other similar gamification design models or frameworks. With different player motivation and design elements frameworks, the application towards personalized gamification design could differ. Table 3 is an example of connecting the obtained preference attributes with the SDT motivation types [10, 36] and the gameful design elements categories [40]. Ideally, each Steam variable can be mapped to a certain type of motivation and a particular gameful design element category. Subsequently, the motivation that drives the corresponding preference attributes and the related gameful design element set can be decided and weighted (e.g., based on relatedness of the variables to the attributes). However, such presumption of connecting attributes, motivation types, and design elements can be subjective, when the motivation of each user towards each individual Steam variable is unknown and hard to be dichotomized. For example, 'Level' is likely to be driven by the motivation of mastery, when, on the other hand, particularly in Steam, higher level means that the user will have more badges and showcases to customize. Therefore, the 'Level' variable is driven by the motivation of autonomy, to some extent. Furthermore, a quantifiable value of ‘Level’, together with ‘Badges’ and ‘Profile Customization’, can be also seen as the tendency towards social comparison. Such equivocality shall be addressed with potential ordering or voting schemes.

5 Discussion

Compared with Lim and Harrell’s study on players’ social identity [22], we cover more perspectives of Steam users’ social behaviors in the gamer community by extending the data collection to more features. However, different from Sifa et al.’s work [38] our data covers only the Steam users’ profile information and not users’ in-game behaviors. Thus, with the current dataset, mapping from the obtained user preferences towards the gameful design elements regarding heavily in-game behaviors, such as, immersion or risk/reward, is not possible [40]. Furthermore, based on the goal of this study to study users’ preference regarding gamification design, the data limits generalization towards all gamification users instead of only gamers. Despite the above limitations, the data (similar to other product-oriented social media profiles, e.g. Amazon profiles) can be seen as more generalized rather than focusing on gamers from specific games or genres. Compared with previous studies on gamification user types [40,42], such data collected from user profiles can be more objective than self-reported survey data.

This study presents a data-driven approach to investigating users’ preferences towards game design elements. The resulting axes of variation among players can be inspected and used in gamification. In future work the results can also be used as a basis for categorization of players; data-driven approaches [16] can improve efficiency and representativeness compared to manually designed categories. One follow-up direction is to build a collaborative filtering recommender system based on similarity of users’ preference towards various game design elements, allowing a personalized gamification design based on the recommendation for each user [41]. Another future direction is to validate the user preference framework with empirical analysis. For example, the user preference scale of Tondello et al. [42] can be adopted as a reference, with Steam users as participants. Furthermore, the data volume can be enlarged with more users, e.g., by crawling from multiple seed users; our data could further be combined with additional data regarding, e.g., players’ in-game behaviors, preference on game genres, and reviews on games. After validation, the proposed user preference framework can be applied to future data-driven player studies. Together with previous gamification design methods [27], the framework will facilitate gamification design and provides an efficient way to address key issues in the user analysis phase [28].

6 Conclusion

We presented an exploratory way of analyzing user presences towards game design elements using Steam user profile data. Using EFA, eight factors/attributes are gained, the value of which can be used to define each individual user’s preference regarding behaviors in the Steam community. Together with the connection between such behaviors and the underlying motivation types and gameful design elements, each user’s preference regarding gamification systems can be also perceived. Due to the quantifiable and objective nature of the data, such estimation of the users' preference can be more precise. It will contribute to the future work of personalized gamification design and creation of recommender systems for personalized gamification in a data-driven manner.

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