Exploring Relations between Personality and User Rating Behaviors

Rong Hu, Pearl Pu

Human Computer Interaction Group
Swiss Federal Institute of Technology in Lausanne (EPFL)
CH-1015, Lausanne, Switzerland
{rong.hu,pearl.pu}@epfl.ch

Abstract. In this study, we conducted an online survey and collected 86 reliable responses on both a personality assessment inventory and ratings retail products ratings, with the aim of investigating whether personality characteristics have an impact on user rating behaviors. Besides personality factors, another four independent variables (i.e., age, gender, previous experience on using recommenders and e-commerce systems) were taken into account when we examined the relationship. The correlation analysis results show that Conscientiousness is negatively correlated with the number of total ratings, category coverage and interest diversity. Individuals high on Agreeableness tend to give more positive ratings. In addition, Gender plays a significant role on all rating behavior variables except percentage of positive ratings. We further explored users' personality profiles along the long tail of the number of ratings. We found that users high on Openness tend to rate more items than required, while low Conscientiousness is a critical factor which provokes users to rate items in an explosive way. Our findings are useful for researchers interested in user modeling, preference elicitation, recommender systems and online marketing.

Keywords. Personality, User Modeling, Rating Behavior, Preference

1 Introduction

Research in psychology has suggested that behavior and preferences of individuals can be explained to a great extent by underlying psychological constructs (or so called personality traits). For example, personality traits have been found to correlate with people's music tastes [1], and impact the formation of social relations [2]. In addition, personality is useful in predicting job success [3] and marital satisfaction [4].

Likewise, in online settings, previous research has shown that certain personality traits are correlated with total Internet usage, preference for different interfaces and with the propensity of users to use social media and social networking sites [5]. More recently, studies have demonstrated that personality characteristics significantly relate to people's social network profiles [6, 7]. Knowing an individual's personality enables us to predict his behavior and preferences across contexts and environments and to enhance user experience by personalizing interfaces and presented information.

In this paper, we are trying to investigate the relations between personality characteristics and user rating behaviors. Modeling users' preferences is one critical step in intelligent systems to tailor personalized services. For example, recommender systems (RS) seek to suggest (or recommend) unseen contents that a user would find to be of interest. A common approach in RS to build user preference models is asking users to explicitly rate items in order to infer their preferences. Therefore, investigating users' rating behaviors could benefit effectiveness and accuracy of user preference modeling [8]. However, to the best of our knowledge, little attempt has been made to relate psychological profiles to user rating behaviors yet.

We conducted an online survey and collected 86 validated responses. The results demonstrate that personality characteristics really have an influence on the way user gave ratings. Besides, gender variable plays a significant role on rating behavior variables. The main contributions of this paper include:

1. Investigate how user's personality characteristics would affect user rating behaviors, comprising of the number of ratings, the number of positive ratings, the categorical coverage of user ratings, and their interest diversity, considering age, gender and previous experience with user rating behaviors.
2. Explore the personality distinction along the long tail of user ratings.

Our results not only provide insights on the effect of user personality characteristics on user modeling, but also suggest practical applications in a variety of areas, including social media websites, e-commerce retailers and recommender systems.

The remainder of this paper is organized as follows. We begin by presenting Big Five Personality model in Section 2, and background and related work in Section 3. We then present our experiment methodology including materials, procedure and participants in Section 4. In Section 5, we describe our dataset by defining the rating behavior variables and independent variables. We provide detailed result analysis in Section 6 and a depth discussion of potential theoretical and practical implications in Section 7 followed by a conclusion.

2 Personality Model

We decided to use the Five Factor Model (FFM, or the Big Five Model) in this study, since it is currently the most widespread and generally accepted model of personality and its ability to predict human behavior has been well studied [9, 10]. This model has been shown to subsume the most known personality traits and provides a nomenclature and a conceptual framework that unifies much of the research findings in psychology of individual differences and personality.

The Five Factor Model divides personality into five dimensional traits: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (OCEAN). Each dimension has its representative characteristics.

- **Openness to experience** measures a person's imagination, curiosity, seeking of new experiences and interest in culture, ideas, and aesthetics.

- **Conscientiousness** reflects the degree to which an individual is organized, diligent and scrupulous.
- **Extraversion** measures a person's tendency to seek stimulation in the external world, company of others, and express positive emotions.
- **Agreeableness** measures the extent to which a person is focused on maintaining positive social relations, reflecting a tendency to be trustful, sympathetic and cooperative.
- **Neuroticism** often referred to as emotional instability, is a tendency to experience mood swings and negative emotions such as guilt, anger, anxiety, and depression.

The five traits have been observed to be genetically heritable, stable over time and consistent across genders, cultures, and races [11]. **Table 1** summarizes the big five personality traits along with their representative descriptive terms for both low and high scorers.

Table 1. Big five personality dimensions and representataive descriptive terms.

Trait	Description	Low scorer	High Scorer
Openness	A willingness to consider alternative approaches, be intellectually curious and enjoy artistic pursuits	Close-minded, Conventional	Imaginative, Curious
Conscien-tiousness	The degree to which an individual is organized, diligent and scrupulous.	Spontaneous, Creative	Organized, Reliable
Extraver-sion	A tendency to be sociable and able to experience positive emotions	Solitary, Reserved	Sociable, Energetic
Agreeable-ness	A tendency to be trusting, sympathetic and cooperative.	Competitive, Assertive	Cooperative, Trusting
Neuroticism	A tendency to experience psychological distress.	Emotionally stable, Self-confident	Prone to negative emotions

3 Background and Related Work

Prior research has shown that personality can efficiently explain a substantial amount of variability in human preferences and behavior across different domains, for example media and cultural preferences [1, 12], and social networking websites usage [6].

According to information processing theory, the satisfaction people derive from outside stimulation, depends on their optimal or preferred arousal levels. One's preference over one item is thought to be affected by the corresponding information processing capacity and affective orientations [13]. Personality is therefore found to be relevant for understanding individuals' appreciation of the arts, for example, paintings and music [1, 14]. Recent research suggested that personality characteristics could be considered as important mediators of media content preferences. Kraaykamp and Eijck [12] examined the impact of the Big Five personality factors on media preferences (TV programs) and cultural participation (book reading and attending museums and concerts). They found that openness clearly encourages an interest in complex and exciting recreational practices. Conscientiousness and friendliness (agreeableness) tend to have negative effects on activities that are either difficult or unconventional, whereas emotional stability negatively influences more predictable means of escape from everyday life. The work in [15] showed that website preferences are influenced by personality characteristics, like those for objects in real world. The authors found that website audiences often have distinct personality profiles, and the relationship between personality and preferences related to website and website categories is psychologically meaningful.

Recently, social media websites (e.g., Facebook, Twitter) have emerged as a major media people communicate with each other and express their personal opinions. Researchers have become interested in how personality impacts user interactions on those social media websites. The work in [16] showed that Extroverts tend to find social media site easy to use and useful. Users are likely to select contacts with similar personality characteristics, and they generally tend to prefer people high in Agreeableness [17]. Current study interests have been more focused on the relations between personality and users' usage behaviors (e.g., the number of posts, likes) and profiles (e.g., the number of friends/followings/followers, age, gender) in social websites [6, 7]. Moreover, increasing attention has been paid on the prediction of personality traits scores based on those publically available behavior and profile information [7, 18].

Golbeck et al. [18] shown that users with different personality tend to use disparate words in their posts and descriptions. Quercia et al. [7] studied Twitter users and found that both popular users and influentials are extroverts and emotionally stable. They further discovered that popular users are 'imaginative' (high in Openness), while influentials tend to be 'organized' (high in Conscientiousness). In [6], Quercia et al. examined the relationship between sociometric popularity (number of Facebook contacts) and personality traits on a different social networking platform, Facebook. They concluded that popular Facebook users tend to have the same personality as people popular in the real world. Similarly, [19] demonstrated a significant connection between personality traits and various features of Facebook profiles.

To the best of our knowledge, few studies have been done on the effects of personality on users' behavior in user preference modeling. In this paper, we are trying to answer this central research question: to what extent does personality factors affect rating behaviors?

4 Methodology

4.1 Materials

We crawled detailed information of totally 18,793 retail products from gifts.com, a gift finder recommender system, covering 44 primary categories (e.g., accessories, alcohol & tobacco, arts & crafts, etc.). The category ontology given by gifts.com is a structure of three levels. For example, under primary category accessories, there contain categories: cufflinks, handbags & briefcases, shoes, ties & suit accessories, wallets & small goods, hats, gloves & scarves and other accessories (so-called sub-category). The shoes sub-category is further divided into casual shoes, dressy shoes and slippers (so-called subsub-category). Thanks to gifts.com, all products have a label for gender. That is, it is known whether one product suits women or men. Using this information, we constraint a user in the product space which contains products match his/her gender. For example, a female user cannot see and rate the products labeled with male. By doing so, we could reduce users' effort on browsing and selecting products to rate. Then, we randomly selected 8 unique products (half for female and half for male if applicable) from each subsub-category to comprise our experimental dataset, which finally includes 871 products.

The Big Five Inventory (BFI, 44 items) [10] was used to assess users' personalities (Big Five Personality Traits) on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree). The Big Five Inventory (BFI) is a self-report inventory consisting of short phrases with relatively accessible vocabulary. Among the 44 items, BFI possesses 16 pairs of items with opposite implications for personality (e.g., "is talkative" and "tend to be quiet"). The responses' consistency on each pair of items was adopted to measure their reliability. The acquisition process takes about 5 minutes on average.

4.2 Procedure

To assess users' personality and collect their ratings, we implemented an online experiment platform. Therefore, participants could easily participated in this study in any place and any time they feel comfortable. In this platform, an online procedure containing instructions, personality assessment questionnaire and rating systems was implemented so that participants could easily follow the task steps. Participants were first debriefed on the objective of the experiment and the upcoming tasks, and then fulfilled the required tasks by following the step-by-step instructions. Participants could exit the experiment anytime they want. The main user tasks contains three steps:

1. Fill in a background questionnaire, including gender, profession, age etc.
2. Accomplish the 44-item BFI personality assessment questionnaire.
3. Select and rate at least 30 items on a binary scale (like or dislike).

4.3 Participants

We recruited participants on the campus (e.g., in library, laboratories, cafeterias and metro station, or via mailing lists) or by announcing our advertisement on Facebook. All participants were also invited to provide an email address to be entered into a raffle for one gift voucher valued at 100 CHF. A total of 122 participants were recruited in our study. We examined their responses' reliability by checking their consistency on the 16 pairs of opposite items possessed by BFI. We filtered out those whose responses have more than 4 inconsistencies among these 16 pairs of items and we ended up having 86 users with reliable responses. The set of those participants is composed of 23 women (26.7%) and 63 men (73.3%). These participants are from 22 different countries (China, Korea, Switzerland, French, etc.), have different professions (student, research assistant, software engineer, company employee, administrative staff, entrepreneur, and so on.). Most of them (74 out of 86) are in the age group ranging from 21-30, 6 users are from age group 0-20, and 6 users are from 31- 40. 23 users have college education background, 58 users have a graduate school education background, and only 4 just graduated from high school and 1 is others. 56% of users (48) have used recommender systems before and among them, 18 users used recommender systems more than 3 times per week. 76% of users (65) have used e-commerce websites to purchase online and 14 users used them more than 3 times per week.

5 Dataset

In this study, we consider the following rating behavior variables.

1. *Number of rated items* (*NRI*). It measures how many items a user have rated, which sometimes closely deal with the accuracy of user preference modeling. For example, the number of items a user has rated directly affect the prediction accuracy of collaborative filtering recommender systems [20]. That is, as the number of ratings number increases, recommendation prediction accuracy can be improved. However, the effect is not monotone. After some point, the accuracy will tend towards stable. In this study, we are wondering which kind of users are following the introductions to only rate 30 items, and who will rate more.
2. *Percentage of positive ratings* (*PerPR*). To build users' preference models, we need to know not only their positive ratings ("like") so as to promote relevant items, but also their negative ratings ("dislike") to avoid irrelevant items. Therefore, it is interesting to investigate how many items will be rated to as "like" out of the whole set of rated items. It is related to how accurate and complete we could know about a user's preference. In this study, we further are interested in how personality would relate to such rating behavior.
3. *Category coverage* (*CatCoverage*). In our rating experiment platform, users are able to select items from one specific category by choosing it from a dropdown list including all of the first level (primary) categories. If a user selects "any category" (default value), shown items are randomly selected from all categories. We are interested in whether users with different personality characteristics will rate items covers a board range of categories, or a narrowed/focused list of categories. Therefore, we utilize the number of categories of rated items as a measure of category coverage. If one item belongs to more than one category, we count it once for each category. There are three levels of categories in our dataset, as described before. We calculate the category coverage for each level. They are indicated as CatCoverage-1 (for primary categories), CatCoverage-2 (for sub-categories) and CatCoverage-3 (for subsub-categories).
4. *Interest diversity* (*IntDiversity*). Different from category coverage, this variable measures the distribution of users' interests in each category. We are interested in whether a user has evenly distributed (diverse) interest in all covered categories, or he has a stronger interest on some specific categories compared to other covered

categories. To answer this question, we adopt Shannon index from information theory as a measure of interest diversity:

$$s = -\sum_{i \in C} f_i \text{In} f_i \tag{1}$$

where C is the above set of categories and f_i is the fraction of items (out of the total number of rated items) that belong to i^{th} category. Similar to the variable category coverage, we consider the interest diversity at three levels, IntDiversity-1, IntDiversity-2 and IntDiversity-3.

Together with the five personality traits, in our study, we take age, gender, and related experiences into account. Previous studies have shown that all of them have an effect on users' behaviors and preferences [12, 21]. Age is measured in three categories, ranging from 0 (0-20 years old), 1 (21-30) and 2 (31-40). Gender is classified into 0 (female) and 1 (male). Frequency of using a recommender system and frequency of doing online shopping are measured at four levels (0: Never, 1: 1-2 times, 2: 3-4 times, 3: over 5 times).

6 Results Analysis

6.1 Correlation with rating behavior variables

We first study the relationship between personality traits and user rating behavior variables, including the number of rated items (NRI), the percentage of positive ratings (PerPR), the category coverage of rated items (CatCoverage-1, CatCoverage-2, CatCoverage-3), and the interest diversity (IntDiversity-1, IntDiversity-2, IntDiversity-3). We calculate the Pearson product-moment correlation between rating behavior variables and personality traits, plus four additional independent attributes, namely age, gender, frequency of using recommender, and frequency of online shopping. The results are reported in **Table 2**.

Conscientiousness is negatively related to the number of rated items (β = -0.177, p < 0.1). That is reasonable since people with high Conscientiousness scores are more responsible for their required tasks. They would carefully select and rate products, and obey requirements strictly. Gender is negatively correlated with the number of rated items as well (β = -0.261, p < 0.05). It means that female participants rated more items than male participants did.

Those who are willing to give positive ratings tend to be high in Agreeableness (β = 0.179, p < 0.1). Agreeableness reflects a tendency to be sympathetic and cooperative. High Agreeableness people tend to be friendly and compassionate to maintain positive social relations, while those low on Agreeableness are less compromise and gullible. Agreeable individuals thus tend to give positive responses to behave friendly.

Personality trait Conscientiousness is found to negatively correlate with the category coverage (CatCoverage-2, b = -0.188, p < 0.1; CatCoverage-3, b = -0.201, p < 0.1).

Conscientiousness reflects the degree to which an individual is organized and scrupulous. Therefore, the covered categories are limited. Moreover, such negative correlation is stronger when the inner category level is considered. We don't find such correlation for the primary categories. In addition, it has been found that gender plays an important role in categorical coverage on all three levels (CatCoverage-1, b = -0.289, p < 0.01; CatCoverage-2, b = -0.247, p < 0.05; CatCoverage-3, b = -0.270, p < 0.05). Negative coefficients mean that female participants rate items within more categories.

Table 2. Correlation coefficients between big five personality traits and rating behavior variables. Statistically significant correlations are in bold and their p-values are expressed with *'s: $p < 0.01$(***), $p < 0.05$(**) and $p < 0.1$(*).

Personality Trait	NRI	PerPR	CatCoverage			IntDiversity		
			1	2	3	1	2	3
Openness	-0.028	0.135	-0.076	-0.021	-0.021	-0.140	-0.061	-0.046
Conscientiousness	**-0.177***	0.107	-0.138	**-0.188***	**-0.201***	-0.044	-0.146	**-0.187***
Extraversion	-0.141	0.059	-0.151	-0.145	-0.151	-0.083	-0.110	-0.122
Agreeableness	0.071	**0.179***	0.042	0.056	0.070	0.016	-0.001	0.042
Neuroticism	0.089	0.030	0.050	0.067	0.078	-0.055	0.034	0.065
Age	0.025	0.049	-0.041	-0.013	-0.029	-0.120	-0.040	-0.076
Gender	**-0.261****	-0.092	**-0.289*****	**-0.247****	**-0.270****	**-0.204***	**-0.192***	**-0.241****
Freq. of using recommender	0.192	0.100	0.057	0.079	0.117	-0.104	-0.034	0.018
Freq. of online shopping	0.136	-0.036	0.029	0.118	0.147	-0.081	0.033	0.102

Conscientiousness is moderately negatively correlated with interest diversity (IntDiversity-3, β= -0.187, $p < 0.1$). That is, high Conscientiousness individuals tend to have low interest diversity. That means most of their ratings focus on a narrowed range of categories. On the other hand, low Conscientiousness individuals tend to have a broad range of interested categories. Likewise, gender plays an important role in interest diversity on all three levels (IntDiversity-1, β= -0.204, $p < 0.1$; IntDiversity-2, β= -0.192, $p < 0.1$; IntDiversity-3, β= -0.241, $p < 0.05$). Negative coefficients mean that female participants rated items covering more diverse categories (interests evenly distributed) than male participants did.

No statistical significant relationships were found between the other independent variables, age and frequency of online shopping, and all the rating behavior variables.

6.2 Personality in different behavior groups

In this section, we look deeper inside at the long tail of the number of ratings. **Fig. 1** plots the distribution of the number of rated items. The x-axis represents the number of rated items, while the y-axis is the number of participants. As we could see from the distribution, most (28 out of 86) of participants only rated the required 30 items. We define this group as "obligation group", since users in area just accomplished the task they asked. Almost equivalent number of participants rated slightly (one or two) more items than the required amount, i.e., 31 items or 32 items. This group is defined as "inertia group", which is potentially influenced by the required number of ratings.

After that, few users rate more. We divide this long tail into two parts with equal number of participants, so that two groups are able to have enough participants to conduct meaningful statistical analysis. We get a reasonable cutting point, 50 ratings. The two groups are called "dispersion group" and "explosion group" respectively, based on the amount of ratings they gave. We are curious whether people from the four groups, representing different rating behavior patterns, vary in personality.

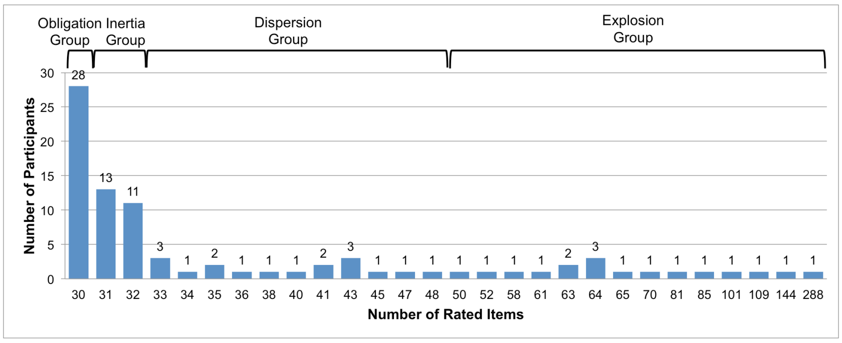

Fig. 1. Distributions of the number of ratings and the division of four behavior pattern groups.

We conducted one-way ANOVA with rating groups as IVs and personality trait scores as DVs, followed by post-hoc pairwise comparisons (Bonferroni) to identify how the four groups of personality characteristics varied from one another. The average scores of each personality traits in the four rating groups are shown in **Fig. 2**.

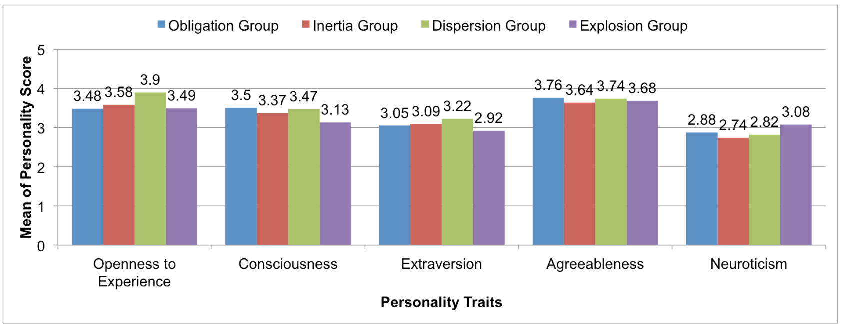

Fig. 2. Mean of personality scores in the four groups.

The ANOVA results indicate significant differences in the personality trait Openness to Experience ($F(3, 82) = 3.171$, $p = 0.029$). Pairwise comparison results show that users in dispersion group scored significantly higher on Openness to Experience (mean: 3.90, SD: 0.33) than those in other three groups, obligation group (mean: 3.48, SD: 0.46; $t = 3.541$, $p = 0.001$), inertia group (mean: 3.58, SD: 0.48; $t = 2.510$, $p = 0.016$), and explosion group (mean: 3.49, SD: 0.58; $t = 2.514$, $p = 0.019$).

Even though there is no statistically significant difference on personality Consciousness among the four groups, we found that users in explosion group have significant higher score than those in obligation group (mean: 3.13, SD: 0.53 vs. mean: 3.50, SD: 0.65 respectively; $t = 2.109$, $p = 0.041$).

With regard to other three personality traits, we didn't find statistically significant differences among groups and between pairs.

7 Discussion

Rating is a major way for users to explicitly express their preferences and opinions. It is critical to understand the nature of rating behaviors and which factors will influence these behaviors. In this study, we investigated the relations between personality and user rating behaviors. Our results have both theoretical and practical implications.

Theoretical Implications. Our results show that low Conscientiousness individuals tend to rate more items, while those with high Conscientiousness scores tend to only rate the required number of items. Similarly, Openness to Experience also affects the number of items a user will rate. However, they are more likely to rate more items in a certain range, probably in order to satisfy their curiosity. Above that boundary, they will stop rating, while low Consciousness individuals will keep rating more. This finding lets us to rethink the validity of ratings a user gives and how to find out those valid ratings. It might be an interesting research in the field of user modeling.

Previous research shows that Agreeableness is positively correlated with the number of friends, groups and "likes" [19]. Consistently, our results show that individuals high on Agreeableness tend to give more positive ratings. It implies that it will be difficult for us to know the actual preferences or opinions of users with high Agreeableness. Consequently, there exists a risk to employ ratings to infer their interests due to the compromised ratings.

Conscientiousness has a negative influence on category coverage and interest diversity. However, those with high Conscientiousness tend to rate items in a limited number of categories and their ratings are likely to focus on certain categories. Diversity is a research top of concern in the realm of information retrieval and recommender systems. It seems that it is much easier to build a diverse profile for an individual with low scores on Conscientiousness compared to those with high scores. Considering the validity issue of ratings, whether such diverse profile will benefit the personalization process is still unknown. Another research question is whether users with high Conscientiousness scores really like a narrowed range of items and how to assist them to rate more diversely.

Gender is another factor that shows a statistically significant correlation with the number of ratings, category coverage and interest diversity variables. However, we didn't find significant correlations between other independent variables (i.e., age, previous experiences on recommender and e-commerce) in our current experiment setting. More exploratory and in-depth experiments are needed.

Theoretical Implications. It is valuable to realize that personality makes an effect on user rating behaviors. It suggests that when intelligent systems, such as social media websites, recommender systems and e-commerce retailers, employ rating data to model users, it is critical to take personality's influences into account. Furthermore, since ratings directly affect the accuracy of inferred user preferences, practitioners and designers can consider designing personalized interfaces to get more useful rating information. For example, Agreeable people are likely to give positive ratings. The interface shown to them could try to motivate them to give true opinions. On the other hand, when practitioners are evaluating their systems, they should avoid those evaluators with high scores on Agreeableness. Gender seems a mediator with strong influence and it is easy to obtain. Therefore, it is necessary to consider this factor in building personalized intelligent systems.

8 Conclusion

We investigated how personality influences users' rating behaviors by an online survey. The correlation analysis results show that Conscientiousness is negatively correlated with the number of total ratings, category coverage and interest diversity. Individuals high on Agreeableness tend to give more positive ratings. Gender plays a crucial role on all rating behavior variables except percentage of positive ratings. In addition, we found that users high on Openness tend to rate more items than required, while low Conscientiousness is a critical factor which provoke users to rate items in an explosive way. The current study was conducted in a small sample size and most participants were students and in the age range of 21-30. In the follow-up study, we plan to continue this study in a platform with more diverse subjects, such as Amazon Mechanical Turk, to obtain more participants with high diversity, with the goal of validating our current findings.

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