Research Article

The Statistical Analysis of Multidimensional Psychological Characteristics and User Feedback Willingness

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The purpose of this paper is to study the influence of multidimensional psychological characteristics on users' feedback intention by using several statistical analysis methods based on information theory. The feedback process can be described as a communication process based on information theory. The feedback information entropy is associated with the degree of uncertainty elimination of the users who provide feedback information. Many factors are related to this uncertainty, such as information senders often stopped feedback process for some reasons and information senders may have provided fake or spam information. In order to encourage more useful feedback information, a model of a user's willingness to provide feedback was established with personality traits and cognitive styles as independent variables, feedback motivation as intermediary variables, and feedback willingness as the dependent variable. 206 online and offline questionnaires were obtained to be analyzed by correlation analysis, regression analysis, and structural equation analysis. Cronbach's α coefficient was used to test the reliability of the questionnaire, and exploratory factor analysis method was used to verify the validity of the questionnaire. First, correlation analysis was used to explore the correlation between personality traits, cognitive styles, and motivation factors. Second, we further explored the strength of the relationship of the five correlated groups of variables through linear regression analysis. At last, we conducted structure equation analyses to test the hypotheses. The results show that both personality traits and cognitive styles can have a significant impact on feedback motivation factors and also show that self-efficacy may be the only evident feedback motivation to encourage useful feedback information. The results show that the willing users with extraversion trait are more likely be motivated by self-efficacy and thus have evident feedback willingness.

1. Introduction

User feedback (*user review*) refers to the behavior of users to deliver feedback information such as their own experience, feature requests, or bug reports of products or services to providers through feedback platforms [1]. Based on the information theory proposed by Shannon [2], we regarded user feedback as a communication process (Figure 1 shows the feedback process based on information theory). In this communication process, the enterprises can be viewed as the receivers receiving feedback from senders who provide feedback message [3]. Enterprises received feedback information via a variety of media, and entropy needs measurement to estimate its validity. In recent years, the technology of Internet and the Internet of Things have grown rapidly, allowing users to provide feedback information via more platforms, such as feedback module in APP, enterprise WeChat, app stores, forums, customer service center, and micro blogs [4, 5].

The feedback information entropy is associated with the degree of uncertainty elimination of the users who provide feedback information. Many factors are related to this
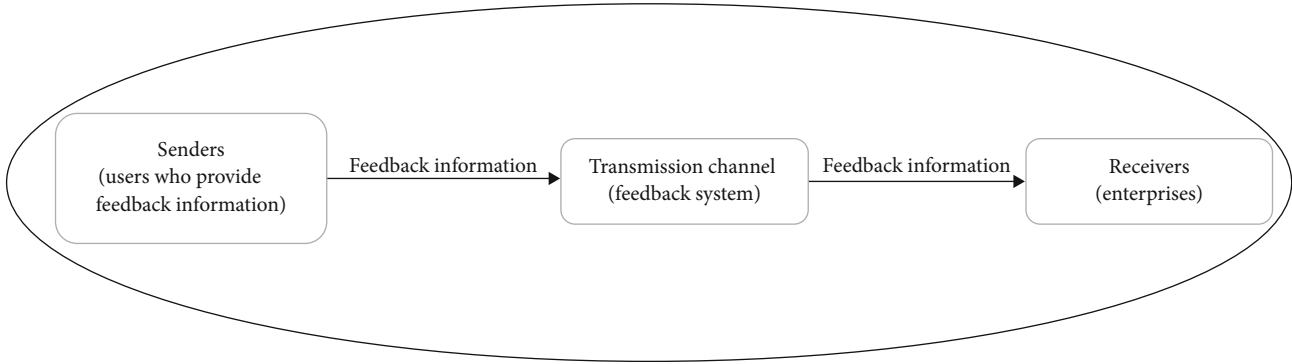
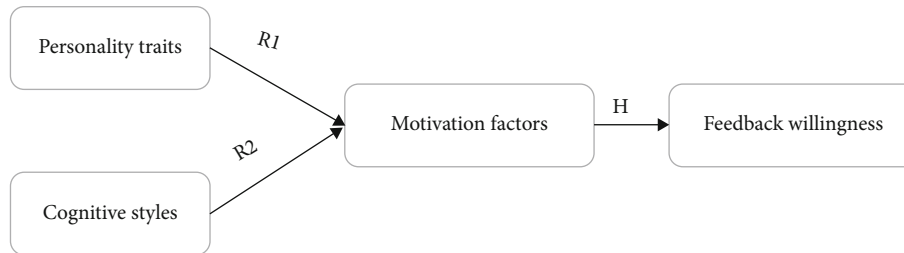FIGURE 1: Feedback process based on information theory.

FIGURE 2: Research model.

uncertainty, such as information senders often stopped feedback process for some reasons and information senders may have provided fake or spam information [6–8].

In order to encourage more useful feedback information in various platforms, it is important to find who are willing to post useful information and understand why they do so. As we know, individual differences in behavior and attitude can be determined by the differences in multiple psychological characters, such as personality traits and cognitive styles, mediated by motivation factors [9, 10]. A few papers have studied the effect of personality traits on user feedback behavior without taking the motivation factors into consideration or only consider single motivation factor [11, 12]. Certain researchers have investigated how cognitive styles influence some online behaviors, such as multimedia perception, online information searching, and creative behavior [13–16], but few have directly discussed the influence of cognitive styles on user feedback. There is a lack of research on the influence of MPC on user feedback.

To address this issue, we develop a conceptual model to discuss the influence of multidimensional psychological characteristics (including personality traits and cognitive styles) on user feedback willingness and also mediate effect of motivation factors in this relationship in the Chinese context (Figure 2 shows the research model). We construct user feedback motivation factors based on social cognition theory [17] and the motivations of consumer reviews [18, 19] that are related to but different from user feedback. We study the conceptual model in two steps. First, we assume that different motivation factors have different degrees of effect on user feedback and identify the effective motivation factors that can significantly make the users generate evident feed-

back willingness to post useful feedback information (Hypothesis 1). We then provide evidence that personality traits and cognitive styles can significantly influence evident feedback willingness as well as demonstrate differences between different traits and styles (Research Question 1 and Research Question 2). This will help enterprises find who are willing to provide useful feedback information according to the corresponding personality traits or cognitive styles and to understand the motivations for doing so.

2. Related Works

Many papers have studied the motivations of *consumer review* (*customer review*, *online review*, and *product review*) which refers to the behavior of consumers who post their own experience information on online platforms after purchasing a product or service. User feedback behavior shares many similarities with customer review in that they are both voluntary behaviors of posting information related to the experience of using a product or service on the platform. Some motivation factors of user feedback can be proposed based on the similarities with customer reviews. First, both customer review and user feedback can help others to some extent. User feedback can help enterprise evolution, and consumer review can help other customers make purchasing decisions. Therefore, we retained the "altruism" factor of customer review [20, 21] as one of the factors of user feedback motivation. Second, "rewards" can be a motivator for both [22, 23]. As for the factor of "a desire to share experience" [18, 22], some feedback platforms, such as the feedback module in APP, enterprise WeChat, and customer service, are invisible to others and may only be visible to

enterprises. Therefore, we did not regard it as a motivational factor for users' feedback. And other factors have little to do with user feedback.

We proposed some other factors based on some other related research and the social cognition theory [17]. Firstly, users may wish that the product or service would be better through their useful suggestions, which would also beneficial to them. By referring to the similar research of Wasko and Faraj [24] on the motivation of contributors to obtain long-term benefits in electronic network practice, we simply called this user feedback motivation factor "self-interest." Secondly, if users' suggestions can be accepted by the enterprise, users would feel that they could have some influence on the decision-making and development of the product or service. Referring to the results of Sundaram et al. [25] on the motivation of influence on other consumers in word-of-mouth communication, we simply call this user feedback motivation factor "influence." Thirdly, users may look forward to getting a sense of accomplishment and approval from the provider for the feedback. By referring to the study of Wasko and Faraj [24] on the similar motivation in electronic network practice, we called this motivation "achievability." At last, we added "self-efficacy" factor based on the social cognition theory proposed by Bandura [17]. Self-efficacy indicates a subjective judgment of the knowledge and ability that users must apply in the process of feedback, such as the judgment of the ability to operate software and express feedback information.

Based on the above analyses, we proposed the following hypotheses:

Hypothesis 1. Availability has a positive effect on user feedback willingness.

Hypothesis 2. Self-interest has a positive effect on user feedback willingness.

Hypothesis 3. Influence has a positive effect on user feedback willingness.

Hypothesis 4. Altruism has a positive effect on user feedback willingness.

Hypothesis 5. Reward has a positive effect on user feedback willingness.

Hypothesis 6. Self-efficacy has a positive effect on user feedback willingness.

2.1. The Influence of Personality Traits on User Feedback Motivations. Allport [26] defined personality traits as the dynamic organization within the individual of those psychophysical systems that determined his unique adjustments to his environment. Personality traits can influence user attitude and behavior [27, 28]. Among the related personality traits' papers, the five-factor model has been recognized by most researchers as the most reasonably individual personality model [29]. The five-factor model was proposed by Gold-berg [30], which included extraversion, neuroticism, openness, agreeableness, and conscientiousness.

Some scholars have discussed the different effects of these five different personalities on behaviors related to user feedback such as information sharing behavior [31, 32] and web service using behavior [33]. Also, some scholars have discussed that users with different personality traits have different degrees of desires for some motivation factors [34, 35]. Some related research showed that extroversion was positively correlated with the willingness to share information [36]. Users with extraversion trait were more likely to engage in comments related to self-actualization and disclosure behavior to help others [37] and were more likely to use web services that were helpful to them [33]. In addition, extroverted individuals had high desires for social recognition, praise, status, and rights [34, 35]. Adaji et al. [11] suggested that extroverted users who posted unhelpful information were susceptible to rewards. Some literature has shown that neuroticism was negatively correlated with personal information sharing, because people with high scores of neuroticism were more likely to be emotional, less likely to trust others, and therefore less willing to contribute their own knowledge [5]. Some researchers found that openness was positively correlated with information sharing behavior. People with high openness were more abstract in thinking and liked to explore new knowledge, and these variables were highly correlated with information sharing [31, 32]. The results of research on conscientiousness and agreeableness were inconclusive, and some research results showed that there was no significant correlation between these two factors and willingness to share [38].

The literature above is about the research on the relationship of personality traits and the motivation factors of some other behaviors related to user feedback. We also wanted to know if the users with five different personality traits would be motivated differently by the feedback motivational factors, so we proposed the following research question.

Research Question 1. Will motivation factors of user feedback be significantly affected by personality traits? Will users with certain personality trait dimension be more likely motivated by some motivation factors?

2.2. The Influence of Cognitive Styles on User Feedback Motivations. Cognitive styles refer to the individual's consistent and characteristic predispositions of perceiving, remembering, organizing, processing, thinking, and problem solving [39]. The Soloman Learning Style questionnaire proposed by Felder et al. [40] has been widely used to test individual cognitive style in four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global) and proven to have good reliability and validity after a large number of practical tests.

Some researchers have investigated the effect of cognitive styles on some relevant online behavior [13, 14], but few of them have taken behavior motivation into consideration. For example, Sangari and Zerehsaz [14] examined the relationship between collaborative information seeking motivation and users' cognitive styles. The results showed that the
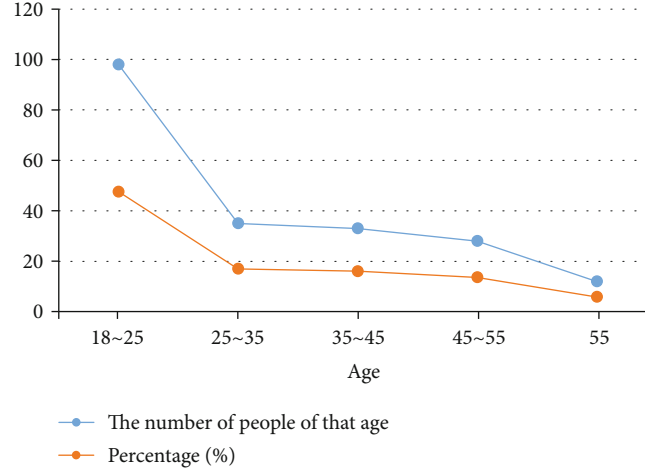
FIGURE 3: Age distribution of the participants.

accommodating style had the highest number of relationships with collaborative information seeking variables. Gulliver et al. [13] showed that cognitive styles can affect information assimilation, self-perceived achievement, and level of self-confidence.

In this paper, we will discuss the relationship between cognitive styles and user feedback motivations. We proposed the following research question.

Research Question 2. Will motivation factors of user feedback be significantly affected by cognitive styles? Will users with certain cognitive style dimension be more likely motivated by some motivation factors?

3. Method

3.1. Participants and Procedure. Online and offline questionnaires were distributed at the same time. Online questionnaires were distributed by sharing the link of Questionnaire Star via project team members' WeChat groups. We sent random WeChat red packet (ranging from *0* yuan to *3* yuan RMB) as online questionnaire reward. And offline questionnaires were distributed on campus and in enterprises in paper form. A part of the offline participants was students from Northeastern University, who were randomly selected in front of the university cafeteria and each received a pen as a reward. In order to better understand the feedback experience of the users who were already working, we selected employees from Hangzhou Chitu Sports Technology Co., Ltd who have a long-term cooperative relationship with us as other offline participants. Each employee participant received a stack of post-it notes as a reward. We obtained ethical approval from all the participants that participation would be anonymous and their responses would be used only for this research. All participants volunteered to take part in this survey and gave informed consent.

We distributed *234* questionnaires in total, and *58* (*24.7%*) online questionnaires, *115* (*49.1%*) offline university questionnaires, and *61* (*26.1%*) offline enterprise questionnaires were returned. After discarding invalid and incomplete cases, there were 206 valid for further analysis.
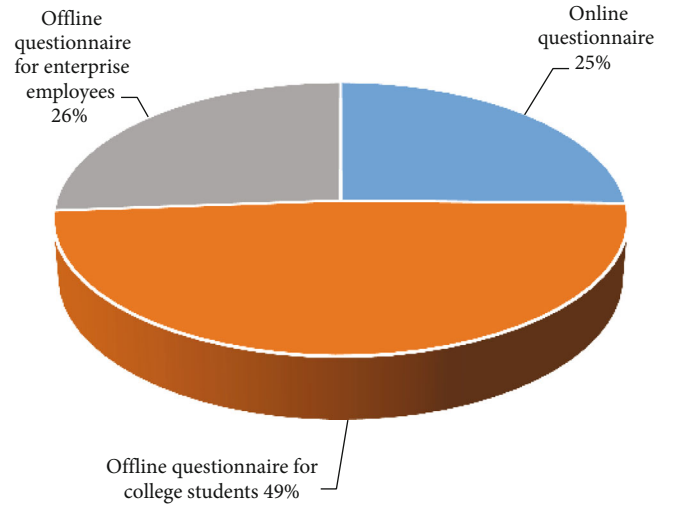

FIGURE 4: Distribution structure of questionnaires.

Among all the participants, 88 (42.7%) were men and *118* (*57.2%*) were women; ages ranged from 18 to 55 years ($M = 29.50$, SD = 5.41) (Figure 3 is the age distribution of the participants; Figure 4 shows the distribution structure of questionnaires).

3.2. Measures. All the measures were presented to the participants in Chinese. Participants rated the items on a *7*-point Likert scale ranging from *1* (completely disagree) to *7* (completely agree). The score of each dimension is the sum of the scores of all items in that dimension. The higher the score, the more prominent the characteristics of the dimension.

Cronbach's α coefficient was used to test the reliability of the questionnaires. The questionnaire data were input into SPSS for analysis. The calculation formula of Cronbach's α is shown in

$$\alpha = \frac{K}{K-1} \left(1 - \frac{\sum_{i=1}^{k} \sigma_i^2}{\sigma_T^2} \right), \tag{1}$$

TABLE 1: The items of motivation factors.

Variables	Number	Items
Achievability	AA1	I look forward to getting a sense of accomplishment from the feedback.
	AA2	I look forward to getting approval from the company for the feedback.
Self-interest	AB1	I give feedback so I can use it more easily in the future.
	AB2	I give feedback to solve my own problems.
Altruism	AC1	I hope that my feedback will prevent other users from experiencing the same problems.
	AC2	I hope that my feedback will improve the experience of other users.
	AC3	I hope the feedback information will be valuable for stakeholder's improvement.
	AC4	I hope the feedback information will be helpful for the product.
Influence	AD1	I want to have some influence on the company decision-making.
	AD2	I hope the product will better meet my expectations.
Rewards	AE1	I look forward to hearing from them after feedback.
	AE2	I expect to get some material reward after feedback.
	AE3	I expect to get some reputation after feedback.
Self-efficacy	BA1	I am confident in my ability to spot problems.
	BA2	I am confident in my ability to express my opinions.
	BA3	I am confident in my ability to operate the feedback system.
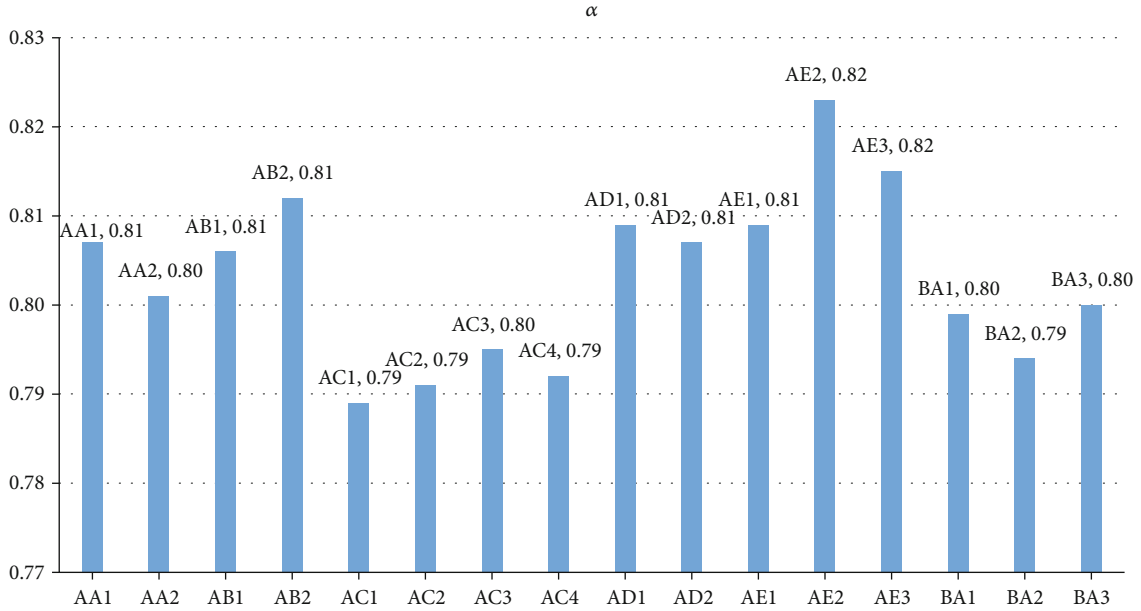
FIGURE 5: Cronbach's α coefficient of each item of motivation factor scale.

where K is the total number of items in the scale, σ_i^2 is the in-question variance of the score of item i, and σ_T^2 is the variance of the total score of all items.

Similarly, the questionnaire data were input into SPSS to verify the validity of the questionnaire, and the exploratory factor analysis method [41] was used to test the data and the formula is shown in

$$\text{kmo} = \frac{\sum\sum_{i \neq j} r_{ij}^2}{\sum\sum_{i \neq j} r_{ij}^2 + \sum\sum_{i \neq j} r_{ij \cdot 1,2\cdots k}^2}, \quad (2)$$

where r_{ij} is the simple correlation coefficient between variables.

3.2.1. Personality Traits. We used the Big Five Personality Inventory (CBF-PI-B) developed by Wang et al. [42] to measure personality traits ($\alpha = 0.871$), which combined the language expression habits of Chinese people; it was adopted due to its good reliability and validity. Sample items include "I often meet with my friend," "I often feel nervous and uneasy," and "I often feel full of energy and vitality."
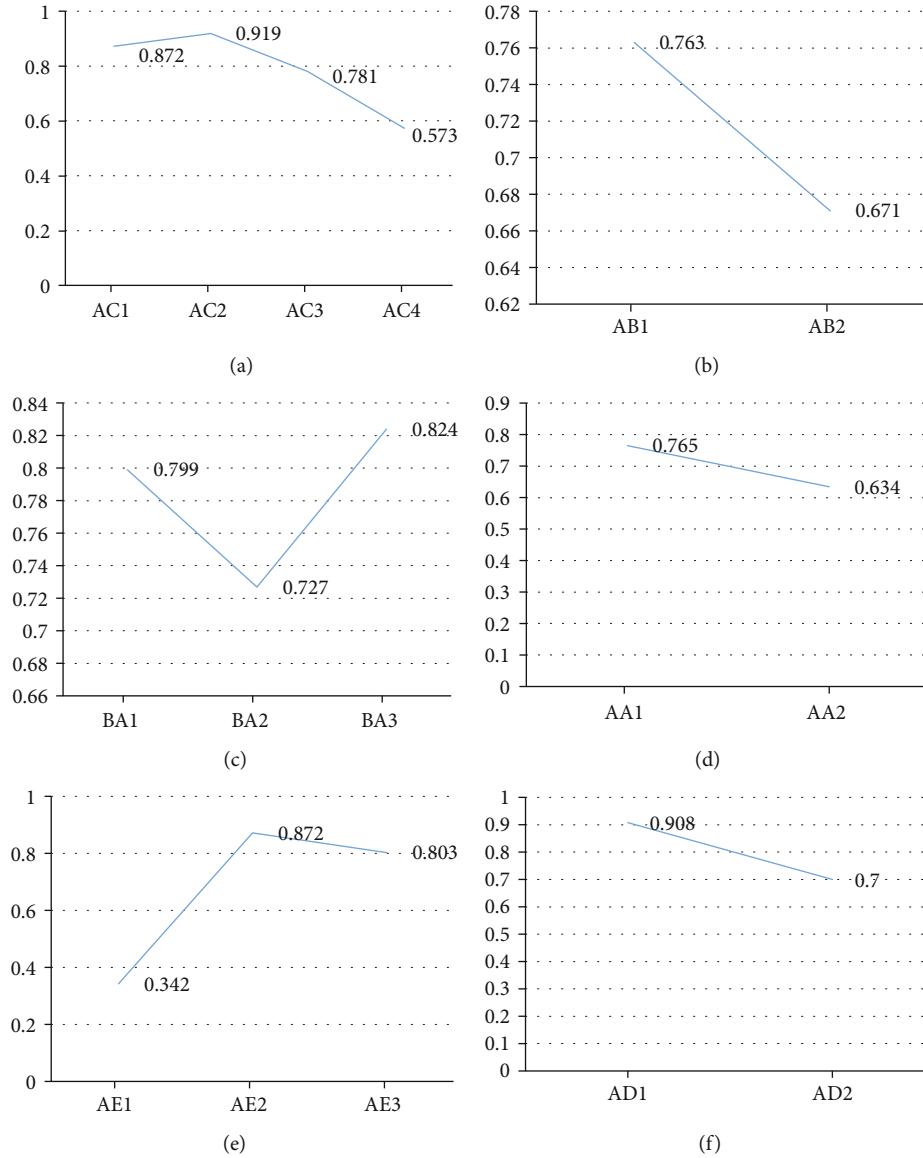
Figure 6: Factor load of motivation factors: (a) altruism, (b) self-interest, (c) self-efficacy, (d) achievability, (e) reward, and (f) influence.

3.2.2. Cognitive Styles. Cognitive styles ($\alpha = 0.865$) were measured using Soloman Learning Style questionnaire [40] in this study. Sample items for cognitive styles are "When things happen, I tend to react quickly on instinct and don't want to think too much," "When I recall done before, is mostly a mental picture in my mind," and "I tend to understand the details of things but not the overall structure."

3.2.3. Motivation Factors. The motivation factors were measured according to a number of relevant papers; the items are listed in Table 1. And the Cronbach α coefficient of each item is shown in Figure 5. The comprehensive Cronbach α coefficient was 0.788, which indicated a good reliability. Also, the questionnaire data were input into SPSS to verify the validity of the questionnaire, and the exploratory factor analysis method was used to test the data. The exploratory factors of each factor are shown in Figure 6. The KOM was 0.779, Sig was less than 0.01, and the cumulative inter-

pretation variance of the six factors reached *74.768%*. With the exception of some measurement errors, the sample validity can thus be considered to be good.

3.2.4. Feedback Willingness. Feedback willingness was measured according to Bhattacherjee [43]. Items include "I am willing to give feedback" and "I am going to give feedback in the future." The questionnaire used a 1-7 Likert scale, with 1 indicating very reluctant to give feedback and 7 indicating very willing to give feedback.

4. Results

4.1. Correlation Analysis. Correlation analysis [44, 45] was used to explore the correlation between personality traits, cognitive styles, and motivation factors. The correlation analysis formula used to calculate the correlation coefficient between any two variables is shown in Formula (3). The

TABLE 2: Descriptive statistics and correlations of study variables.

	M	SD	1	2	3	4	5	6	7	8	9	10	11
(1) Gender													
(2) Age	24.50	5.41	0.05										
(3) Neuroticism	27.33	7.65	0.16	0.09									
(4) Conscientiousness	34.89	5.24	0.13	0.16	0.05								
(5) Agreeableness	34.52	5.83	0.42*	-0.09	0.16	0.09							
(6) Openness	34.96	5.32	0.06	0.13	0.13	0.16	0.08						
(7) Extraversion	30.42	6.22	-0.05	0.18	0.12	0.09	0.03	0.13					
(8) Active/reflective	-1.88	4.33	0.18	0.12	0.06	0.13	0.11	0.09	0.24				
(9) Sensing/intuitive	2.97	4.28	-0.12	-0.10	-0.05	0.18	0.21	0.13	0.12	0.16			
(10) Visual/verbal	4.65	3.36	0.16	0.09	0.18	0.12	-0.11	0.14	0.21	0.03	0.07		
(11) Sequential/global	0.89	4.85	-0.08	0.12	0.12	-0.10	0.05	0.11	0.01	-0.04	0.12	0.13	
(12) Achievability	4.13	1.55	-0.05	0.18	0.16	0.09	0.12	0.12	0.23**	0.01	-0.03	-0.06	0.03
(13) Self-interest	5.88	0.92	0.53*	-0.15	-0.08	0.12	0.02	-0.03	0.08	-0.06	0.24**	0.03	0.13
(14) Altruism	4.56	1.23	0.49*	-0.10	-0.05	0.18	0.12	0.13	0.22**	0.23**	-0.16	0.11	0.03
(15) Influence	4.96	1.24	-0.31	0.11	0.10	0.10	-0.03	-0.10	0.12	0.08	0.04	0.06	0.12
(16) Rewards	4.98	1.13	0.05	0.07	0.12	-0.10	-0.11	0.11	0.01	-0.04	0.09	-0.06	-0.16
(17) Self-efficacy	4.99	1.54	0.16	0.09	-0.30**	0.10	0.08	0.11	0.44**	0.18	-0.00	0.13	0.10

Note. $N = 206$. $^{*}p < 0.05$. $^{**}p < 0.01$.

TABLE 3: The results of linear regression analysis.

Variables	Achievability	Altruism	Self-interest	Self-efficacy
Model	1	2	3	4	5
Intercept	2.69**	4.34**	3.33**	5.65**	3.64**
Extraversion	0.05*		0.04*		0.06**
Neuroticism					-0.02
Sensing/intuitive				0.06*	
Active/reflective		0.07*			

Note. $N = 206$. $^{*}p < 0.05$. $^{**}p < 0.01$.

questionnaire data were imported into SPSS for correlation analysis using the Pearson correlation coefficient [46–48]. Table 2 shows means, standard deviations, and correlations for the study variables.

$$r = \frac{\sum XY - (((\sum X)(\sum Y))/n)}{\sqrt{\left(\sum X^2 - ((\sum X)^2/n)\right)\left(\sum Y^2 - ((\sum Y)^2/n)\right)}} \\ = \frac{E(XY) - E(X)E(Y)}{\sqrt{D(X)}\sqrt{D(Y)}}, \qquad (3)$$

where X and Y are variables and n is the number of the variables.

Through the correlation analysis, the five groups of variables were correlated, which were neuroticism, extraversion on self-efficacy, extraversion on achievability, extraversion on altruism, sensing/intuitive on self-interest, and active/reflective on altruism.

4.2. Regression Analysis. We further explored the strength of the relationship of the five correlated groups of variables through linear regression analysis [49, 50]. The calculation formula of linear regression analysis is shown in Formula (4) [51, 52]. Table 3 shows the results of linear regression analysis. The data from Table 3 can answer questions 1 and 2. We can infer that the users with extraversion personality trait may be more likely to be positively motivated by self-efficacy, altruism, and achievability. The users with neuroticism personality trait may be more likely to be negatively motivated by self-efficacy. The users with sensing/intuitive cognitive style may be more likely to be positively motivated by self-interest.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon, \qquad (4)$$

where y is the variable being interpreted, x is the explanatory variable, ε is constant, and β is the coefficient.
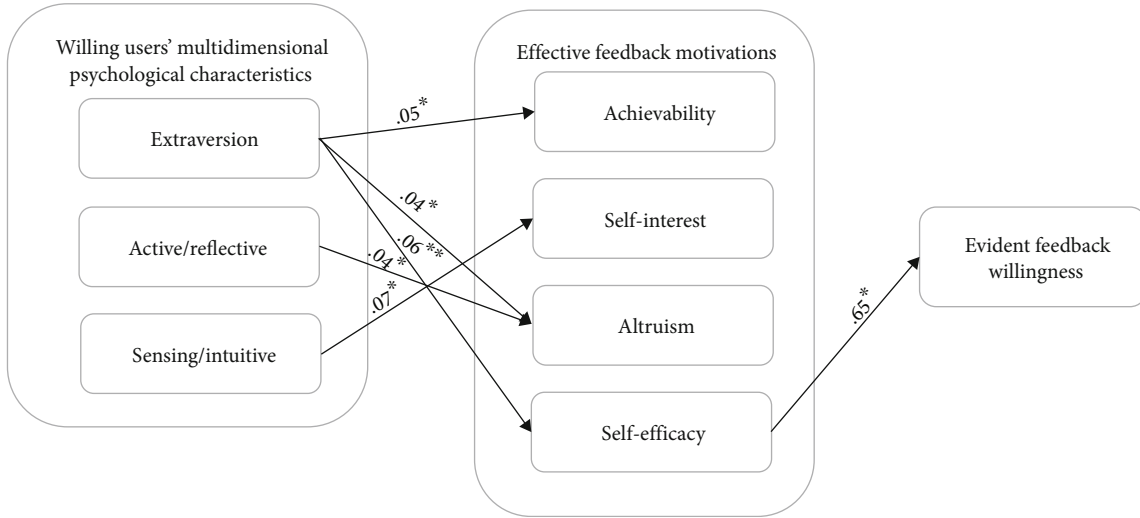
FIGURE 7: The final model. Note: $^*p < 0.05$; $^{**}p < 0.01$.

4.3. Relationship between Motivation Factors and Feedback Willingness. We conducted structure equation analyses to test Hypotheses 1–6 [41, 53]. The data were imported into AMOS 22.0 for analysis [54, 55]. According to the analysis results, CMIN/DF was *2.06* which met the required standard (ranging from *1* to *5*), GFI > 0.9 (the calculation can be seen in Formula (5)) [56], AGFI > 0.8, RMSEA < 0.08, and CFI > 0.9 [51]. We can see that all the absolute fitting indexes of the model met the required standard [57, 58], indicating that the model has a good fitting degree.

$$ \text{GFI} = 1 - \frac{F}{F_b}, \tag{5} $$

where y is the F is the value of the fitting function and F_b is the value of the fitting function obtained when $\Sigma = 0$.

The results of structure equation analyses showed that only the path from self-efficacy to feedback willingness (estimate = 0.65, $p = 0.004 < 0.05$) meets the required standard [41, 59]. Therefore, Hypothesis 6 was supported.

4.4. The Final Model of User Feedback Willingness. Based on the results of correlation analyses, regression analyses, and structural equation analyses, the final model was obtained. Figure 7 demonstrates the path from "willing users' multidimensional psychological characteristics" to "effective feedback motivations" to "evident feedback willingness" with all the supported hypotheses. The loading factors of variables in the final model were marked on each arrow.

As we can see from Figure 7, the only one critical path was obtained, namely, "extraversion"–"self-efficacy"–"evident feedback willingness," which indicates that users with extroverted trait are more likely motivated by self-efficacy and thus have evident feedback willingness.

5. Discussion

In this study, we aimed to provide evidence concerning the influence of multidimensional psychological characteristics

(including personality traits and cognitive styles) on feedback willingness, by examining motivation factor as a mediator of this relationship. We separately investigated the influence of psychological characteristics on motivation factors and which motivators can produce evident feedback willingness. The results show that both personality traits and cognitive styles can have a significant impact on feedback motivation factors, and there are differences among different traits and styles.

The results also show that self-efficacy may be the only evident feedback motivation to encourage useful feedback information. Hypothesis 6 is supported. At last, the critical path from "extraversion" to "self-efficacy" to "evident feedback willingness" is obtained, which indicates that the willing users with extraversion trait are more likely motivated by self-efficacy and thus have evident feedback willingness.

5.1. Theoretical Implications. We have contributed to the literature in several ways. First, we have systematically investigated the effect of personality traits on user feedback willingness by considering as many motivation factors as possible, which is in contrast with previous research that did not consider motivation factors [11] or only consider single motivation factor [12]. Our research discovered the personality traits of the willing users and evident feedback motivation factors, which provided theoretical support for the establishment of an effective feedback platform. The effective incentives of feedback platforms can be designed based on evident feedback motivation factors; the preference of the feedback interaction can be designed based on the personality traits of willing users. The results of our research showed that the willing users with extraversion trait were more likely to post useful feedback information, which is consistent with the research results on the influence of personality on information sharing behavior. Related research indicated that extroverts were more likely to express themselves and talk to their supervisors [44], or extroverts were more likely to engage in online activities related to comments and retweets [37].

Second, we extended the research of the influence of cognitive styles on behavior motivations. Previous researchers have studied the effect of cognitive styles on some online behaviors, such as multimedia perception [13], online information searching [14], and creative behavior [15], but few studied the effect on behavior motivations. The results of our research showed that the cognitive styles can influence the motivation factors and there are differences between different styles in the field of user feedback. Our research showed that sensing/intuitive style is more likely motivated by self-interest factor and active/reflective style is more likely motivated by altruism factor.

5.2. Practical Implications. These results can provide some practical guidance for enterprises. Our results showed that the users with extraversion trait are more willing to post useful feedback information, so enterprises can focus on extroverts to participate in online or offline user survey when they want to improve their products or service. For example, they can invite extroverts to be participants for interview, focus groups, questionnaires, etc. Enterprises also can send online feedback questionnaire links and feedback request emails to export-oriented users. In contrast to previous extensive and random user surveys, which invited a large number of users who were not willing to provide useful feedback, such a screening of users can save costs and ensure the effectiveness of the information obtained. Our results also showed that what motivated extroverts to post useful feedback information was self-efficacy, and then, enterprises can pay more attention to establish incentives based on self-efficacy.

5.3. Limitations and Directions for Future Research. There are two main limitations in this study. First, as we used a cross-sectional research design, we cannot infer causality between the study variables. Second, our research only concluded that the users with extraversion trait are more likely motivated by self-efficacy, while for enterprises, they may do not know how to find the extraverts and how to establish incentives based on self-efficacy. Therefore, we will study how to identify the personality traits of users based on big data technology and discuss how to establish effective incentives based on self-efficacy motivation factor in user feedback platforms.

Data Availability

The simulation experiment data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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