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MATCHING RELATION BETWEEN CONSUMER'S PSYCHOLOGY AND DIGITAL GOODS RANKINGS

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Abstract. The development of digital goods has profoundly changed the economic relationship and trading methods. Among all the digital goods recommendation information, ranking information is of prominent significance. The rankings impact consumers positively as they make decisions on buying digital products. We serve rankings and consumer psychologies as the object of this study, and will offer references and suggestions for the customization of the mobile terminal. Combining factor and cluster analysis, we subdivide the rankings into three groups first based on consumers' values and lifestyles: reputation ranking, consumption behavior ranking and purchase intention ranking. Then, we use a correspondence analysis method to conclude the matching relationship between different types of rankings and various consumption psychology groups.

Keywords: ranking, digital goods, consumer psychology

1. Introduction

Along with the development of the digital economy, trading on the network platform will become mainstream in the future. The methods of recommending digital goods change accordingly with the trading. It appears that online reviews and charts are currently the main ways used for making recommendations. Because there are increasingly online reviews made by sellers to improve their reputations, the online comments made by consumers tend to lose value. On the other hand, rankings, as the manifestation of commodity information and persuasive data, provide consumers with intuitive commodity sales statuses, sales prospects and popularity levels. Increasingly more businessman are paying attention to the rankings of products and applying that information. We believe that this study on digital commodity rankings will play an important role in promoting the development of a digital goods recommendation system.

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2. Literature review

With the growing prosperity of the digital economy, the operation of digital goods is of extremely high economic value. Accordingly, the promotion and sales of digital goods are receiving increasing attention. Rankings, as one of many recommended methods of digital goods, have a prominent effect and accordingly, become a major research focus. In recent years, numerous scholars have conducted studies related to ranking and consumer psychology and have achieved fruitful results.

Website ranking is a focus of research in the current e-commerce field, while an additional class of research is based on the long tail theory [1]. The main thought of the theory is that the ranking of the goods could drive sales of slow-moving merchandise. The article How Does Popularity in the Information Affect Choices in a Field Experiment elaborates that the top selling products generate more traffic. However, some special consumer psychology theories posit that customers may choose other services not ranked but provided by the same merchant [2]. Yet another class of research reveals the promotion mechanism behind the ranking for merchandise sales. Some literature notes that good sales of e-commerce merchandise combined with network reviews and rankings will receive more benign evaluations and better sales results [3]. Another article indicates that ranking, as a form of non-personalized advertising, when used in conjunction with product deployment can result in significant sales of the targeted product by a large number of consumers [4]. The article Collaborative Filtering with Ordinal Scale-based Implicit Ratings for Mobile Music Recommendation discusses that on the intelligent mobile terminal, the explicit and implicit reviews play a key role in the sales of digital music [5]. There is also research that focuses on the ranking evaluation model and its evaluation methods. They propose a probabilistic graphical model which contains an unobservable latent variable that affects all other observable variables, and is applied to ranking evaluation of institutions using a set of performance indicators [6].

In the traditional market, consumer psychology is divided into six categories. These include novel personalized consumer psychology, planning and practical consumer psychology, health and brief consumer psychology, traditional consumer psychology, quality consumer psychology, and symbolic consumer psychology [7]. In the e-commerce environment, psychological characteristics of the customer include proactive demand, rational consumer behavior, demand for the convenience of purchase, pursuit of the shopping experience and focus on individual consumption [8]. With respect to the development of e-commerce, online consumer psychologies can be divided into two categories, the psychological factors that promote the development of e-commerce (the pursuit of the cheap, evading reality of interference and the pursuit of individuation) and the restrictive factors that impede consumer online consumption (violations reducing consumer trust, lack of security of personal privacy, online payments and inefficient distribution logistics). Corresponding with consumer psychology, this article describes three types of consumer behaviors in the e-commerce area. These include wide range selection, rational price choice and expression on product requirements [9].

As previously noted herein, research on ranking focuses on the mechanism of ranking with respect to the promotion of digital products. However, the research standings from the perspective of consumer psychology are rare. In the merchandise sales process, rankings, as purchase information, link merchants with consumers and act as a bridge for realizing the value of commodities. Accordingly, commodity betrayal is the first morphological change of the commodity. The buying behavior of the consumer as it relates to a specific good will directly affect the realization of the commercial value of the good [10]. In this sense rankings play a significant role by influencing consumer psychology and purchase behavior. This study will further advance the process of ranking digital goods.

This study explores the preferences of consumers with different psychological characteristics for different types of rankings and discusses the various influences that rankings have on consumer groups. The first part of the article consists of a literature review; the second part discusses the research design and sample collection; the third part presents the factor analysis, cluster analysis and correspondence analysis of online consumer psychology to distinguish the effect of different types of rankings on different segments of consumers; the fourth part describes the research findings and analyzes the differences in the rankings for digital goods among the various consumer segments that possess varying psychological consumer behaviors.

3. Research Design

According to market research results, domestic online digital goods are basically at no cost. Based on this fact, we decide to focus on the degree of customer attention toward digital goods during the course of the study, while not directly focusing on customer buying behavior, to measure customers' decision-making practices. In addition, in identifying the digital goods market, we find that the market lacks vitality. College students are the most active customers in the market; therefore, the participants in this study are mainly university students. This can be extended to other social groups, however.

According to preliminary analysis results, we develops a questionnaire. Based on Sproles and Kendal's article A Methodology for Profiling Consumers' Decision-Making Styles [11], we develops a corresponding scale and creates the first edition of the questionnaire. The questionnaire scale uses a 5-point Richter evaluation method whereby 1 equates to strongly agree and 5 means strongly disagree. Using the initial version of the questionnaire, a small-scale pre-test is conducted. Taking the representativeness of the test into account, a sample of 200 students from Beijing University of Posts and Telecommunications are surveyed. After collecting and analyzing the data, we find that the questionnaire is credible and effective. Taking into consideration the feedback from the respondents, the team modifies and simplifies the format and content of the formal questionnaire to be used in the study.

The content of the questionnaire is broken down as fig.1. The first part consists of questions related to the matching between rankings and digital goods. The second part consists of questions that are based on consumer psychological tendency theory and are intended to determine the psychology of the respondents. The third part asks questions to determine the ranking type preferred by the survey respondents. The fourth part consists of personal questions regarding the respondents' demographics. Figure 1 displayed the research process.

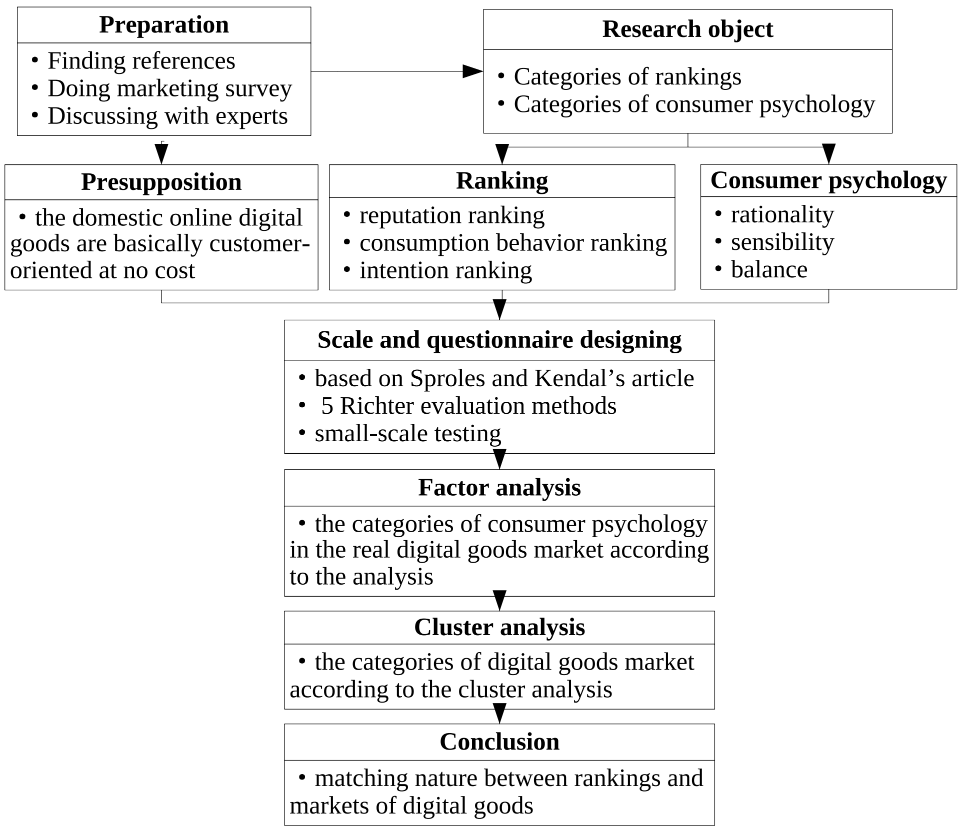

Figure 1. The Research Process

The main survey method adopted for this study is the questionnaire survey. Samples are collected randomly from colleges and universities in Beijing in early October 2011. In the course of the investigation, 500 questionnaires are distributed, and 451 are collected. Through strict examination, 349 questionnaires are determined to be valid. The collection rate of the questionnaire turns out to be 77.38%.

The survey results from the 451 returned questionnaires consist of variables, such as ranking tendencies and consumer psychology, and demographic information about the respondents, such as gender, grade and average monthly living costs. Among the sample, the male to female ratio is 59:41, and the percent of freshmen, sophomores, juniors, seniors and graduates is 8.6%, 25.2%, 25.8%, 22.9%, and 17.5%, respectively. The sample also covers various income groups. Overall, the samples could represent the college population.

By using Cronbach's alpha as the testing criterion, the research team determines there is internal consistency among the questionnaire statements. As evidenced from the reliability analysis result, the correlation coefficient of the data was 0.754 (greater than 0.7), indicating that the design of the questionnaire is ideal.

4. Data Analysis and Research

In this part, the study analyzed the data with the methods of factor analysis, cluster analysis and correspondence analysis.

Firstly, KMO value and Bartlett's sphere detector method was used to determine if the data was suitable for factor analysis. By analyzing the factors, the study picked up 4 factors which were rational factor, sensible factor, balance factor and hesitant factor.

Secondly, on the base of the factor analysis result, the study do the cluster analysis and the result turned out that consumers psychologies could be divided into 3 catalogues, including intellectual type, casual type, integrated type. Each catalogue represented one kind of market with different consumer psychology.

Thirdly, a correspondence analysis analyzing the correspondence between markets and rankings was done to figure out the relationship between consumer's psychology and digital goods rankings

4.1. Clarification of the consumer psychology variables in the market of digital goods

Consumer psychology tendency variables are distributed into three categories and 18 dimensions. We use SPSS.20 software to conduct a factor analysis of the data and to turn complex variables into small number factors representing clear relationships.

The study use kynurenine monooxygenase (KMO) value to tell whether the data is suitable for factor analysis. KMO value shows the strength of the relationship between two random variables or two signals [12]. The relationship between KMO value and data correlation is shown in Table 1.

Table 1. Relationship between KMO value and data correlation

KMO value	0.9-1.0	0.8-0.9	0.7-0.8	0.6-0.7	<0.6
Correlation	Very strong	Strong	Medium	Week	Rather week

The analysis results reveal that the KMO value is 0.772, which is greater than 0.5, indicating that the data are suitable for factor analysis.

Meanwhile, using Bartlett's sphere detector method, which is for checking whether each variable independently, the Sig. value is found to be 0.000, indicating that the hypothesis is rejected. If the hypothesis is rejected, the factor analysis can be done, or these independent variables may not suitable for factor analysis. Variables can be considered dependent, and integrated factors can be extracted from eighteen variables. The research analyzes the factors using the principal component analysis method, and the orthogonal rotation method under varix criterion is used to rotate and integrate the score matrix of the analysis results. Using an eigenvalue greater than 1 and an absolute value of the factor loan greater than 0.4 as the selection criteria, we remove part of the data. After doing so, we obtain the results as shown in Table 2, which includes the factor load after the orthogonal rotation.

Table 2. Rotational component matrix

	Component			
	1	2	3	4
a1	.620			
a2		.642		
a3				.407
a4	.596			

a5		.749		
a6	.527			
a7	.420			.403
a8		.655		
a9				.796
a10	.549			
a11	.510	.448		
a12	.454			.491
a13				
a14		.606		
a15			.737	
a16	.436		.418	
a17			.614	.524
a18			.490	

Extracting method: principal component analysis
Rotation converged after 9 iterations.

For the data to be distributed randomly, the questionnaire was designed as 18 dimensions of scale randomly distributed. We delete variables that display an unclear taxonomic status, and extract four factors based on the explanations given below. The integrated rotational component matrix is shown in Table 3.

Table 3. Integrated rotational component matrix

Factors / Factor Variables	Ration-al	Sensibl-e	Balanc-e	Hesita-nt	Dimensions of variables
I am cautious when shopping online, and I think before I make my decision.	0.62				Rationality
I will not buy a commodity that has little actual use even it looks splendid.	0.596				
I think no payment, no gains. As low prices do not mean that the commodity deserves buying, I will not buy it.	0.549				
If there is a new product launched, I will always be the first buyer surrounding me.		0.642			Sensibility
I am casual and straightforward when shopping online. I will buy a commodity as soon as I like it.		0.749			
If the good I want to buy is relatively the same as what the people around me bought, in order to be consistent with the masses, I tend to buy it.		0.655			
My shopping flow is as follows: make a shopping list according to the commodity cost-effectiveness and purchase the one I like the most.			0.737		Balance
I often buy commodities that look very pretty or make me feel comfortable.			0.614		

I will pursue the pop stuff, but if the things are not of reasonable price, I will not buy them.	0.49		
I tend to measure many factors before deciding to buy, including the brand, benefits, quality, personal and emotional effects, etc.		0.407	Hesitancy
I always desire to buy a commodity because I am keen on it, but finally give up because it is of low cost-effectiveness.		0.796	
Even when many others have spoken highly of a commodity, as long as I do not like it or it does not look good, I will not buy it.		0.491	

Explanations for the above factors are as follows:

B1 rational factor: This factor represents a rational psychological tendency in shopping. When consumers who have such psychological tendencies are shopping, they will focus their attention on the actual value of the goods and measure the effect the commodities have on themselves. They always shop rationally rather than comparing blindly with others.

B2 sensible factor: This factor represents a sensible psychological tendency. Consumers who receive a high score in this area often rely on their own feelings rather than on the practical use of the commodity. They tend to shop casually and straightforwardly and often buy goods that are of little use to them.

B3 balance factor: This factor represents a balanced psychological tendency. Consumers who receive a high score in this area often comprehensively consider various factors. Additionally, they do not think too much about their own feelings or about external factors, and they often balance many factors when shopping. They often buy goods that fit their taste and are cost-effective.

B4 Hesitant factor: This factor represents a hesitant psychological tendency. Various studies regarding consumer psychological classification divide consumer psychology into rational consumer psychology, sensible consumer psychology and balanced consumer psychology. While our research is based on this theory, we find that in the digital market, consumer psychology should be a fourth classification, termed hesitant consumer psychology by our team. This particular phenomenon has characteristics representative of the digital economy. Due to the wealth of information available, any type of digital market contains a considerable amount of information about the publicity of the website publicity, the presentation of the business and the reviews of consumers. Consequently, information redundancy will impact consumer decision making. The most significant feature of these types of consumers is that they will analyze a large amount of information about the commodity for a significant period of time, they will consider a large number of factors, and they will be significantly influenced by the information available on the website and by the various comments made by other consumers.

4.2. Classification of consumer markets on the basis of consumer psychology variables conducted by the cluster analysis

In this part, the four consumer psychological factors are analyzed using the K-means cluster method, which results in three cluster centers. The clustering results are shown in Table 4.

Table 4. Three cluster center

	Cluster center		
	1	2	3
B1	.34100	.10200	.17480
B2	.00000	.62000	.00000
B3	.20563	.00000	.12280
B4	.00000	.00000	.52420

The cluster analysis is based on four factors, all of which are determined by a factors analysis. The three cluster centers are perceived as three digital goods markets. According to the corresponding factors, each of the three cluster centers is explained as follows:

Cluster center 1: intellectual type. This consumer receives the highest score for B1, the rational factor, followed by B3, the balanced factor. This consumer receives a zero for each of the other two factors. These consumers tend to be rational in their daily lives. Therefore, they tend to take a rational approach when choosing digital goods. Thus, we refer to them as the intellectual type.

Cluster center 2: casual type. This consumer receives the highest score for B2, the sensible factor, followed by B1, the rational factor. This consumer receives a zero for the other two factors. These consumers tend to live a casual life and rely more on feelings when buying digital goods. Thus, we refer to them as the casual type.

Cluster center 3: integrated type. This consumer receives the highest score for B4, the balance factor, while receiving either relatively low scores or zeroes for the other three factors. These consumers think everything through and are very thorough in their daily lives, focusing on all aspects of all factors. They may sometimes think too much or even hesitate for too long. Thus, we refer to them as the integrated type.

4.3. Correspondence analysis of the consumer market and digital goods ranking

Based on the above data analysis, we develop a general classification of consumer psychologies regarding the market of digital goods, and by applying the cluster analysis method, the digital goods market is divided into three types. By collecting a significant amount of ranking information and by referencing numerous articles, we divide rankings into three categories: reputation ranking, consumption behavior ranking and purchase intention ranking. To determine how the markets and rankings align and correspond with each other, we analyze the corresponding matches of three digital goods markets and three categories of rankings based on questionnaire data and on the results of the data analyses presented in this study. The results are shown in figure 2.

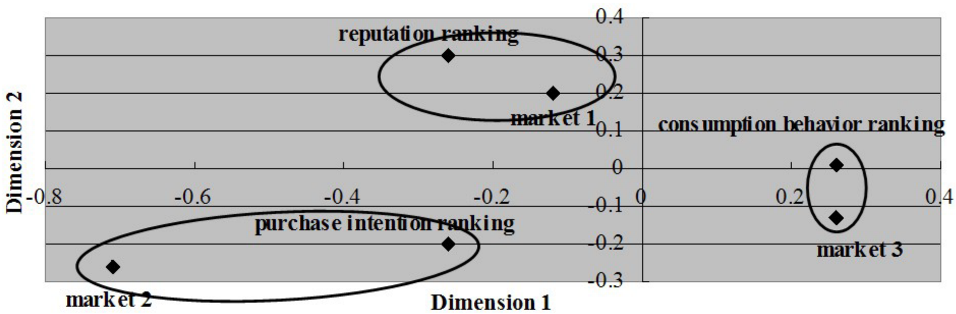

Figure 2. The Corresponding Match Between Rankings and Digital Goods Markets

As evidenced in Fig.2, there are certain corresponding match relationships between and among the three digital goods markets and the three categories of rankings.

The figure reveals the following:

- Matching relationship between market 1 and reputation ranking. Market 1 is composed of the intellectual type; thus, consumers in this market are mostly of the rational type. Consumers tend to pay a lot of attention to the practical value of the commodity itself, and they are particularly sensitive to utility and value. Reputation ranking mainly relies on comment ranking, follower ranking and recommendation ranking, and these ranking are based on subjective information and statistics. This type of ranking is consistent with consumers' rational psychology in market 1, which is to buy overflow goods. Thus, market 1 is consistent with reputation lists.
- Matching relationship between market 2 and purchase intention ranking. Market 2 represents random markets. When shopping, consumers in this market often depend on their feelings, and they tend to pursue the more novel product, showing concern about the changes in the product. They also tend to follow the popular trend. Purchase intention ranking includes top-search ranking and collection ranking. These rankings are established according to the dynamic changes in the product information and in consumers' feelings. Accordingly, the corresponding populations are more casual. As the purchase intention ranking matches the consumer psychology of market 2, market 2 is matched with purchase intention ranking.
- Matching relationship between market 3 and consumption behavior ranking. Market 3 is an integrated market where consumers demonstrate a balanced and rational consumer psychology. They are good at considering various factors accompanied with a lot of hesitation, and they shop in accordance with the collective value of the standard. Meanwhile, they are not overly sensitive about prices, but they are hesitant when making purchasing decisions. Consumption behavior ranking includes bestseller ranking and soared ranking. Furthermore, it is based on whether the trade was successful as information embedded in the merchandise sale can reflect universal customer acknowledgement. This type of ranking provides adequate recommendation information that is needed by consumers in market 3, as such information can assist consumers in deciding whether to buy a commodity. Thus, market 3 matches consumption behavior ranking.

As evidenced from the analysis results, for consumers of different consumer psychologies, there are obvious differences in concerns about various rankings. This is because basic shopping decisions differ among consumers who have different consumer psychologies. The information needed for the various rankings differs as well. Different types of rankings contain different aspects of the commodity information and therefore meet different information needs of consumers. Consumers tend to focus on the types of rankings that can provide references and information needed for making decisions, which is why we are able to match the various types of rankings with the various types of consumers.

5. Conclusion

Due to the excessive wealth of information, consumer recognition biases significantly influence consumer purchase behavior. As the manifestation of the statistical summary of product information, rankings are the result of intuitive merchandise sales, sales prospects and the results of consumer evaluations. Accordingly, all of these factors help consumers to quickly grasp the commodity information quickly. However, as consumers possess different consumer psychologies, they view the rankings differently. Thus, the major ranking structure on the Internet must also be modified.

The research first divides the consumer psychologies into four main factors (rational factors, emotional factors, balanced factors, and hesitant factors) using the factor analysis method. A cluster analysis of the four factors is then conducted, which leads to three clustering centers: the rational center, the arbitrary center and the integrated center. Each of these centers represents a digital goods market that is then distributed according to different consumer psychologies. The study performs a correspondence analysis among the three clustering centers and the three rankings to better determine the matches between the different digital markets based on consumers with different types of digital goods rankings.

This study finds out the matching relationships between markets and rankings, thus emphasizing the practical significance of the analysis regarding ranking concerns. Accordingly, digital goods merchants and websites can select various rankings based on the target customers to optimize the ranking recommendation structure, which can significantly benefit the merchants. At the same time, this tendency also provides a reference for the introduction of operators' personalized services for different consumers. With respect to the merchants, they can introduce the reputation ranking for rational consumers when selling cheap digital goods of good quality, recommend the purchase intention ranking to arbitrary consumers when selling software and games with dazzling appearances, and suggest the consumer behavior ranking for hesitant and following consumers. On the other hand, the consumers can select the best ranking structure based on their personal consumer psychology to purchase the most suitable digital goods for their needs. Consumers with different psychologies are concerned with different types of rankings. Therefore, the analysis regarding the corresponding relationship between consumer psychology and types of rankings can help customers to purchase the appropriate digital goods in less time and at a lower price. In addition, as the trading turnover rates and customer satisfaction rates increase, the profit for mobile operators will also increase.

College students are main purchasers of digital goods. The analysis of the relationship between consumption psychology and the effect of digital goods ranking on college students is of great significance, which is the reason college students are selected as the respondents in this study. Because of certain restraints, only college students in Beijing are surveyed. Students from other vocations and educational degrees are not included in this study. Therefore, to some extent, the results of this study are restricted.

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