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Cognitive Computation on Consumer's Decision Making of Internet Financial Products Based on Neural Activity Data

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Abstract. Internet finance has become a popular business in today's society. However, different from the physical objects or services sold online, Internet financial products are actually contracts defined by financial terms which make customers bear the possibility of capital losses and liquidity restrictions, but they can obtain profits in the future with some uncertainties. This paper takes consumer's cognition in the decision making of Internet financial products as research circumstances, studies the above issue by conducting an EEG-fNIRS experiment, and proposes an effective cognitive computation method based on neural activity data through BP-GA algorithm. On this basis, a new recommendation approach of Internet financial products is explored according to consumer's typical shared mental model. The computing and testing results indicate that researches of this paper provide promising new ideas and novel methods for the cognitive computation of artificial intelligence and the recommendation of Internet financial products.

Keywords: Internet Finance, consumer preferences, cognitive computation, mental model, neural activity data, artificial intelligence.

1. Introduction

With the rapid development of Internet and advanced mobile technology, Internet finance (ITFIN), a new financial business model, has developed vigorously and is generally accepted by the vast number of consumers in today's society [1]. During the past ten years, Internet finance has provided various new businesses and products such as third-party payment, crowd funding, P2P (Peer-to-Peer lending), Internet financial portal products and so on [2, 3]. Internet finance can serve many useful purposes, bring more convenient service experience, meet the diverse needs of the consumers, and also improve the operation efficiency of traditional business. Internet technology has revolutionized financial markets, which has a significant impact on reducing the transaction cost, extending financial services, improving time efficiency and bringing a proliferation of innovative Internet financial products and services. However, the wide range of new financial products and services can also make consumers confused when choosing the suitable products. Different from the physical products sold on the Internet, Internet financial products usually involving complex financial terms, which may contain various risks. The selection of Internet financial products is a decision-making process which involves consumer's financial needs, cognitive characteristics, consumption experience, risk preference, etc [4].

Previous studies have shown that consumers' cognition and preferences, as the most important psychological factors in their mental models, play a leading role in the decision-making of their Internet financial products [4, 5]. Therefore, how to analyze the above factors and conduct a successful recommendation to customers has become the focus of researchers. In this respect, various methods and technologies commonly used in traditional e-commerce are also applied to Internet financial products. These methods and technologies are usually based on data mining or questionnaire survey of consumers' online behavior [6, 7]. However, the influencing factors and cognitive characteristics of consumers' decision-making on Internet financial products are quite different from those of traditional products in terms of profitability and risk risks [1, 3, 4, 5]. Without considering the intrinsic neural mechanism underlying the consumer's cognition and behaviors, it is difficult for traditional methods to achieve accurate and reliable results [8, 9].

In this paper, the cognition of consumers in the decision-making process of Internet financial products is studied through a neural experiment, aiming to explore an effective cognitive computing method based on neural activity data, so as to improve the recommendation performance according to different mental models of consumers. It is organized as follows: Section 1 introduces the background and motivation of our research; Section 2 reviews the related research work; Section 3 conducts a neural experiment and proposes the customer's cognitive computing method based on neural activity data; Section 4 analyzes the consumers' mental model and explores a new recommendation approach; and Section 5 undergoes summary and discussion of this paper.

2. Related Work

2.1. Consumer's Consumptive Behaviors of Internet Financial Products

Consumers' behaviors and their influence on financial market belong to the research field of behavioral finance theory. According to the traditional theory, consumers have limited rationality, limited ability of information processing in decision-making, but with less consideration of the psychological influences on behaviors. New financial behavior theories, such as prospect theory and emotional psychology theory, have brought human's psychology and behaviors into the research framework of finance [10]. Those theories study individual behavior and psychological motivation from a micro-perspective to explain and predict the development of financial market, effectively making up for the shortcomings of traditional financial theory.

Financial consumption is also a psychological process related to consumers' investment beliefs, preferences and decisions. Unlike the physical objects or services that can be experienced immediately, financial products are contracts defined by financial terms, which have the possibility of making customers bear capital losses and liquidity restrictions, but may make some uncertain profits in the future. Different from general products or services, customers of financial products should consider factors related to financial profitability, liquidity, and risk and so on in their decision making [4]. On the other hand, as irrational people, customers' inherent psychological and cognitive biases may lead them to make inappropriate judgments on market trends and product risks [11, 12]. In fact, they are easily misled by the exaggerated marketing strategies of the trading platform in Internet financial transactions. If consumers are unable to understand the existing information provided due to cognitive bias, they may suffer economic losses after making improper decisions. Therefore, consumers' cognition of Internet financial products decision-making is quite distinctive and situational, which needs further research in order to recommend appropriate products according to different preferences.

2.2. Consumer's Cognition of Decision Making in Cyber Space

Through literature review, we found that most of the existing researches on cognitions of consumers' online decision making are based on data mining or questionnaire survey. They obtain consumers' survey data and online behavior data, and establish models to analyze the cognitive characteristics and influencing factors of consumers. For example, Cui et al. studied the consumer satisfaction and trust through the online comment extraction and semantic analysis of emotional words [7]. Wang and LV used data mining and K-means clustering algorithm to analyze the preferences of different consumers for commodities [13]. In addition, text feature extraction technology, principal component analysis, EM clustering and other technologies have also been applied.

Jiang et al. analyzed the stakeholders and related topics according to the differences of information writing style and content characteristics of social media [14]. Social media variables are extracted from two aspects of information activity intensity and sentiment tendency, and a regression prediction model is established to analyze the impact of social media activities on stock behaviors. Experiments on Yahoo Financial Forum show the effectiveness of the proposed method. Besides, some scholars began to build behavior prediction model from user emotional information. These methods provide an effective way to study consumers' cognition based on self-report or behavioral data. However, they may be suffered by the influences of some subjective elements, such as inconsistencies and inaccuracies in description, behavior and intention mismatch and so on [15]. It seems that the customers' cognitions can't be fully and accurately explained if only through historical behavior data analysis or questionnaire survey, so we need to further explore its internal cognitive mechanism. Therefore, cognitive computing is considered as one of the key technologies to deal with big data challenges and better navigate big data analysis. [16].

The preliminary conceptual framework of cyberspace psychology was proposed by John Suler in his hypertext book of “The psychology of cyberspace” in January 1996 [17]. It is intended to understand the behavior of individuals and groups in cyberspace. Cyberspace psychology is a discipline that studies the psychological phenomena and related laws of people’s online behaviors. In the modern information society, physical space and cyberspace are increasingly closely tied. Users’ understanding, experience, values, and ideology can be mirrored in their behaviors in cyberspace. For the sake of having a better understanding of the relationship between different spaces, Dai studied the evolution mechanism of social public emergencies, and first presented a comprehensive framework of CyberPsychosocial and Physical (CPP) computation based on social neuroscience mechanism in 2014 [18, 19]. CyberPsychological computing (CPC) is developed under the framework of CPP, and it aims to quantitatively study the relationship between the user’s internet behavior and its mental states, so as to establish a computing model. CPC has already been applied in the cognitive interpretation concerning user behaviors in cyberspace. For example, Zhou et al. computed the attention, interest, emotion, and satisfaction of learners according to the learner’s online actions of keyboard and mouse based on the prior knowledge of neural mechanism [17].

2.3. Consumer Mental Model of Product Design and Recommendation

The concept of mental model was firstly proposed by Craik in 1943[20]. It is basically used to describe the inner psychological activities and internal cognitive processes conceived and projected by human thought, which affect people’s comprehension, interpretation and view of their own behavior. As an effective design method, mental model has been well applied in product and service design. For example, it can be used as a design method to improve understanding between product suppliers and consumers [21]. Mental models can also suggest how to react and adapt to new situations. In many cases, knowledge can be better coordinated, communicated and shared among heterogeneous multidisciplinary teams based on the shared mental model [22, 23]. Through different process incentive mechanism, Turumugon *et al.* showed that mental model can make product meet the expectations of different users by adopting “localization” and content analysis method [24].

Mental model theory can be used as a paradigm to identify, measure and model end-users’ privacy attitudes, concerns, intentions and behaviors. It can also provide a valuable structure to investigate connection between privacy related online behaviors and provide valuable insights into privacy decisions [25]. In addition, mental model can identify gaps and misunderstandings in order to develop effective communication. For instance, it can be used as a tool to reveal the basic principles of collision insurance, in which the budget income of consumers is predicted across consumption categories. The results show that consumers’ purchase of insurance is a normal commodity and follows a cognitive model that emphasizes budget constraints [26]. As for the mental models of customers in the decision-making of Internet financial products, there are still many issues worthy of further study. It is difficult to accurately find the cognitions of consumers if only through data mining of their online behavior data. With the help of advanced neural experiment technology, we can study the cognition of consumers based on neural activity data, extract the typical mental models which may exist in the consumers' decision making of Internet financial products, and then obtain valuable prior knowledge for recommendation.

3. Experiment and Cognitive Computation

3.1. Neural Mechanism of Consumer's Cognition

Based on the existing research results of neuroscience, we proposed the neural mechanism of consumers' cognition and decision-making of Internet financial products, as shown in Figure 1.

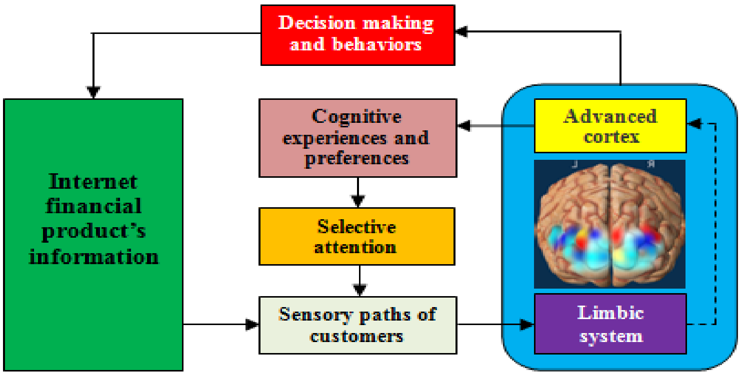

Fig. 1. Neural mechanism of cognition and decision making

When consumers perceive the information of Internet financial products through the sensory path, a series of neural activities from the limbic system to the advanced cortex of consumers' brain may be triggered. First of all, the expressive features and interesting points of financial products will generate preliminary cognition through the limbic system. At last, cognitive experience of external information forms rational cognition by advanced cortex. In this process, consumers' cognitive experience and preference for previous similar products can regulate sensory paths of attention resources and time allocation through the neural activities of advanced cortex, thus affecting their selective attention. The customers' decision making and behaviors are the result of their judgment influenced by the above neural activities in the brain.

The above neural mechanism provides the basis of psychological pattern for consumers to make decisions on the choice of Internet financial products. Among them, the expressive features and interesting points of products can attract consumers' initial attention, but their final decisions making are mostly based on rational cognition. According to the existing studies [1, 2, 4], consumers' cognition of Internet financial products can be summarized into following four aspects: convenience, profitability, liquidity, and risk. The above cognition will be affected by a variety of consumer personal factors and environmental factors, such as age, gender, education level, experience, product reputation, herd behavior, and so on. Our cognitive computing does not focus on the relationship between consumers' cognition and the above factors, but aims to explore the methods to compute consumers' cognition of convenience, profitability, liquidity, and risk from their neural activity data. There have been a lot of researches related to human cognition, involving the dynamic and complex neural activities of brain function network [28], which is hard to be well described with a clear mathematical model. Therefore, we employ the BP-GA algorithm to realize the cognitive computing as shown in Figure 2.

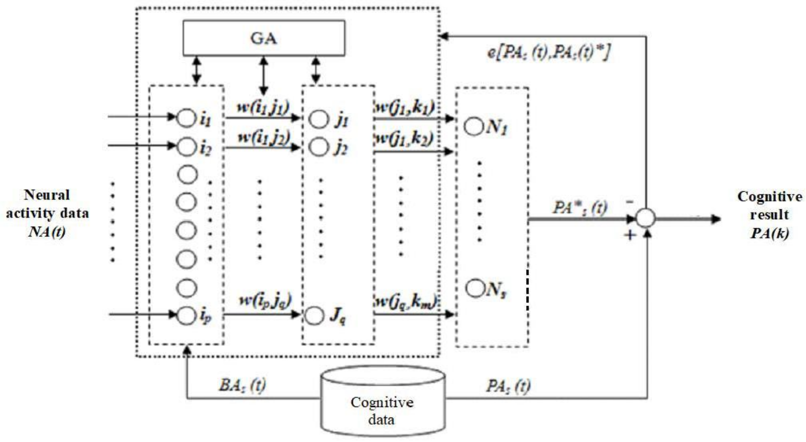

Fig.2. Cognitive computation with BP-GA algorithm

The input variable $NA(t)$ is the multi-dimensional time series data of neural activity, which represents the consumers' cognitive responses in their brains. It consists of a set of feature parameters $f_1(t), f_2(t),..., f_M(t)$ extracted from the data collected by neural experimental equipment.

$$NA(t) = [f_1(t), f_2(t),..., f_M(t)]. \tag{1}$$

The output variable $PA(k)$ is the result of consumer cognition composed of four parameters PA_1 , PA_2 , PA_3 and PA_4 , which represent convenience, profitability, liquidity, and risk respectively. In human cognitive research, there are a variety of neural activity data available for application. Among them, EEG (Electroencephalograph) and fNIRS (functional Near Infrared Spectroscopy) data can be collected by portable devices, which are widely used in the actual environment. EEG has superior dynamic performance, and fNIRS can better reflect the spatial characteristics of neural activities by detecting the concentration changes of oxygenated (HbO) and deoxygenated hemoglobin (HbR). In order to improve the accuracy, we use the multi-modal feature parameters of EEG-fNIRS composite data as the input variable $NA(t)$ for cognitive computing.

3.2. Experiment and Cognitive Computation

Alipay launched a financial product “Yu’E Bao” in 2013, which can be operated and transacted by mobile phone. It has been an innovative Internet financial product with huge number of consumers. Similar to Yu’E Bao, we design eight Internet financial products for testing, as shown in Table 1, which reflect different degrees of convenience, profitability, liquidity, and risk. Convenience represents how easy it is for consumers to fully understand product information and complete a transaction operation. Its degrees are set to highest, high, medium, low, or lowest for each product respectively.

Table 1. Internet financial products for test

Product No.	Convenience (Degrees from highest to lowest)	Profitability (Expected annual rate of return)	Liquidity (No-redeemable days)	Risk (Maximum Possible Loss)
1	highest	1% fixed	0	0%
2	high	2% fixed	30	0%
3	medium	3% fixed	180	0%
4	low	5%	7	10%
5	low	20%	30	20%
6	medium	50%	60	30%
7	High	100%	180	80%
8	lowest	200%	360	100%

In our experiment, we set up a mobile phone to display the test signals of the above products. The neural activity data of consumers’ cognition is recorded by EEG-fNIRS device and converted into the input variable of BP-GA computation procedure. Figure 3 shows the experimantal data collection and processing.

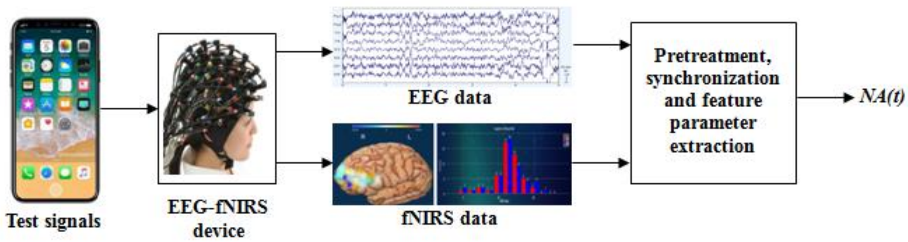

Fig. 3. The experimental data collection and processing

In the cognitive and decision-making study of EEG fNIRS, every specific test task should be carried out according to the strict experimental paradigm. Generally, only one influencing factor can be considered in a task. The purpose of the task is to find out the characteristics and mechanisms of neural activities significantly related to the above influencing factors. However, the goal of our study is to explore an effective method of consumer cognitive computing from their neural activity data. Therefore, we designed the experimental paradigm as follow:

$$\text{Product information(60s)+Black screen(1s)+[Question(10s)+Answer(10s)]}_{1\text{-}4} \quad (2)$$

Product information comes from the eight design products in Table 1, but it appears in random order. The test steps of [question (10s) + answer (10s)] are carried out four times. In each cycle, consumers are required to assess the convenience, profitability, liquidity, and risk of products with a score from 1 to 10 respectively. Since consumers' cognition before decision-making is mainly reflected in the thinking process of the question, we only extract the neural activity data during the period of [Question(10s)] to generate the input variables calculated by BP-GA, and take the data during the black screen (1s) as its deviation. Take the consumer evaluation score during the period of set [Answer(10s)] as the output variable calculated by BP-GA. According to the experience of preliminary experiment, the input variables are composed of the following multimodal feature parameters: wavelet decomposition coefficient of EEG signal, mean value, variance, skewness coefficient, kurtosis coefficient and slope of fNIRS signal.

We conduct this experiment with total 38 consumers of Yu'E Bao, including 22 males and 16 females. They are between the ages of 18 and 54 with the educational level from junior college to Ph.D. The consumer's evaluation score of convenience, profitability, liquidity, and risk of each tested product is between 1 and 10, of which 10 represents the highest level and 1 represents the lowest level. At the end of this experiment, the consumers give the degree of purchase intention for each tested product according to their preferences based on the above scoring method. After that, we randomly select the data of 26 consumers for training, and use the remaining data of 12 consumers for computation test. Figure 4 shows the change of its relative error with the number of iterations.

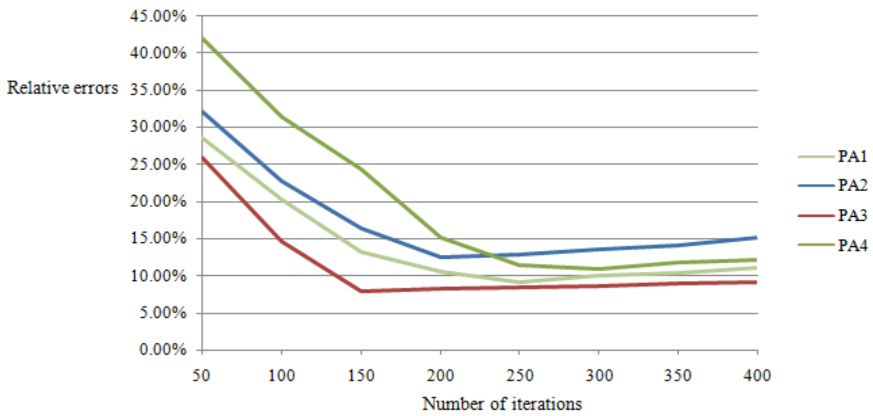

Fig. 4. The change of relative error with the number of iterations

As we can see from Figure 4, the optimal number of iterations for parameters PA_1 , PA_2 , PA_3 and PA_4 are different. Furthermore, Table 2 shows their minimum relative errors at the optimum number of iterations.

Table 2. The minimum relative errors with optimal number of iterations

Parameters	Minimum errors	Optimal number of iterations
PA_1	8.8%	237
PA_2	12.4%	216
PA_3	7.7%	162
PA_4	10.8%	307

Table 2 indicates that the cognitive computing method based on customer's EEG-fNIRS neural activity data can achieve a high accuracy from 87.6% to 92.3%. In the traditional method, the above parameters are usually evaluated by consumer's subjective self-report. Because of the fuzziness and inaccuracy of consumers' feelings and descriptions, it is difficult to accurately reflect the implicit cognitive characteristics of consumers. Our method also provides an objective way to calibrate the cognitive state of consumers.

4. Mental Model and Recommendation Approach

4.1. Mental Model

Consumers' cognitions and their decision making of Internet financial products are usually affected by a series of individual factors such as age, gender, education level, experience, income, personal preference and psychological characteristics. However, consumer psychology research shows that consumers with similar cognitive and decision preferences may have a common mental model. In order to extract the potential sharing mental model of Internet financial product consumers, we explained the structural equation model of variable relationship, as shown in Figure 5.

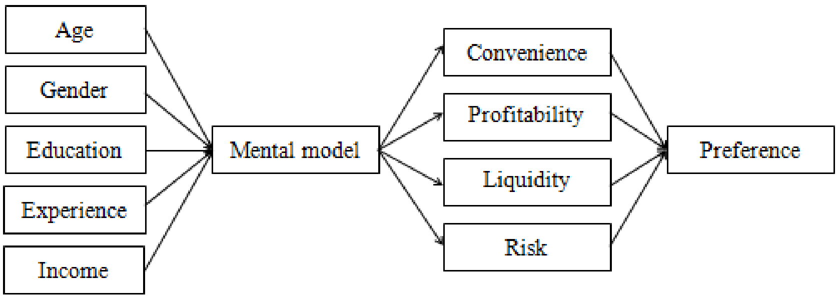

Fig. 5. Structural equation model of variable relationship

The mental model of consumers is determined by age, gender, education, experience, income and other personal factors. It affects consumers' cognition and behavior.In this case, we can see different evaluation of convenience, profitability, liquidity, and risk of Internet financial products, as well as different decision preferences. Among them, the comprehensive influence of consumer mental model on preference can be summed up as the cognitive characteristics of convenience, profitability, liquidity, and risk. Therefore, we conducted cluster analysis on the above four parameters of the experimental participants. The consumers' evaluation scores of (Convenience), (Profitability), (Liquidity), (Risk) and the Preference scores can be divided into the most appropriate five clusters by the ant colony optimization clustering algorithm [29, 30]. Table 3 shows their clustering and analysis of variance.

Table 3. Clustering and variance analysis

Parameters	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	*F*-value	Sig.
PA_1	8.234	8.012	4.132	6.010	3.212	32.774	.000
PA_2	4.455	9.231	8.312	8.281	9.278	58.918	.000
PA_3	8.391	6.034	6.055	7.003	2.329	27.625	.000
PA_4	1.052	8.297	8.291	8.135	9.116	127.479	.000

Table 3 indicates that there are five typical cognitive patterns exist in customers on the decision-making of Internet financial products as follows:

- **Pattern 1:** high convenience, medium profit, high liquidity, and low risk, corresponding to Cluster 1;
- **Pattern 2:** high convenience, high profit, medium liquidity, and high risk, corresponding to Cluster 2;
- **Pattern 3:** low convenience, high profit, medium liquidity, and high risk, corresponding to Cluster 3;
- **Pattern 4:** medium convenience, high profit, medium liquidity, and high risk, corresponding to Cluster 4;
- **Pattern 5:** low convenience, high profit, low liquidity, and high risk, corresponding to Cluster 5.

Actually, the above patterns also reflect the typical shared mental models of customers while they make the decisions of Internet financial products. Although, the similar cognitive patterns may possibly be found by the traditional methods such as data mining of consumer's online behaviors or questionnaire survey, however those patterns in our study are extracted from the customers' neural activity data, which not only verify the existing traditional research findings based on neural mechanism interpretations, but furthermore provide precise descriptions of customers' cognitive characteristics as well as the important prior knowledge for customer's analysis and product's recommendation.

4.2. Recommendation Approach

In the field of online recommendation, a variety of intelligent recommendation methods have been proposed. Especially the recommendation method based on collaborative filtering algorithm has been widely used in financial product recommendation because of its high efficiency and good performance [31, 32]. The basic idea of collaborative filtering is to assume that customers who have similar interests or often choose similar products may have similar preferences [33]. It exists some problems such as cold start, scalability, sparsity and so on, and is in continuous improvement [34, 35]. However, we believe that the lack of consideration of the internal cognitive mechanism of consumers is an important defect. On this basis, a novel method of Internet financial product recommendation based on consumer mental model is proposed as follows:

- **Step 1:** Classify the categories of recommended products. There are many kinds of financial products, such as banking products, insurance products, stocks, futures, etc., but consumers usually tend to focus on one or several products of interest. Therefore, product category is the first factor to be considered. In fact, the test products designed in our experiment are shown in Table 1, covering all the common categories of Internet financial products, and the recommendation should be put forward based on the analysis of the same category.
- **Step 2:** Calculate the parameters of the recommended product. This step is performed by the following formula:

$$PA_{ij} = c_{ij} * PA_{ib}, i = 1,2,3,4; j = 1,2,3,...,M. \quad \textbf{(3)}$$

In the above formula, PA_{ij} is the degrees of convenience (PA_{1j}), profitability (PA_{2j}), liquidity (PA_{3j}), and risk (PA_{4j}) of the recommended product j, where j=1, 2, 3…,M; c_{ij} is the ratio coefficients of product j obtained by comparing with the most similar product of the same category in Table 1; PA_{ib} is the consumers' average score for the above comparison products in our test. Finally, the values of PA_{ij} for all M products considered as recommended should be standardized in the range of 1 to 10, which reflects the characteristics of the products.

- **Step 3:** Identify the customer's shared mental model. For new consumers, this calculation will be based on the historical data of the products purchased by that consumer. Refer to Step 2, first compute the degree PA_{ih} (*i=1, 2, 3, 4; h=1, 2, 3…, N*) of N products purchased by consumers in history. Then, the following Euclidean distance function is used to identify the consumers' shared mental model through pattern recognition:

$$d_m = \|PA_{ih} - PA_{im}\|, i = 1,2,3,4; h = 1,2,3,...,M; m = 1,2,3,4,5. \quad \textbf{(4)}$$

Where, d_m is the Euclidean distances between PA_{ih} and the five typical shared mental models, as shown in Table 3 respectively; and PA_{im} is the similar center values of cluster m (*m=1, 2, 3, 4, 5*) in that table. Because for different product categories, the value of cluster center may be different, so PA_{im} should be calculated according to the same product category to which PA_{ih} belongs. Finally, the shared mental model of consumers is determined to be the lowest to the highest possible level d_m.

- **Step 4:** Realize personalized recommendation. The values PA_{ij} obtained in step 2 represent the characteristics of those products to be recommended. The obtained values of d_m in Step 3 reflect the degree of closeness between the new consumers and the tested consumers in the experiment, which are described by Euclid distance of five clustering centers of different typical sharing mental models. Therefore, we design the personalized recommendation approach for new consumers based on the above relationship, as shown in Figure 6.

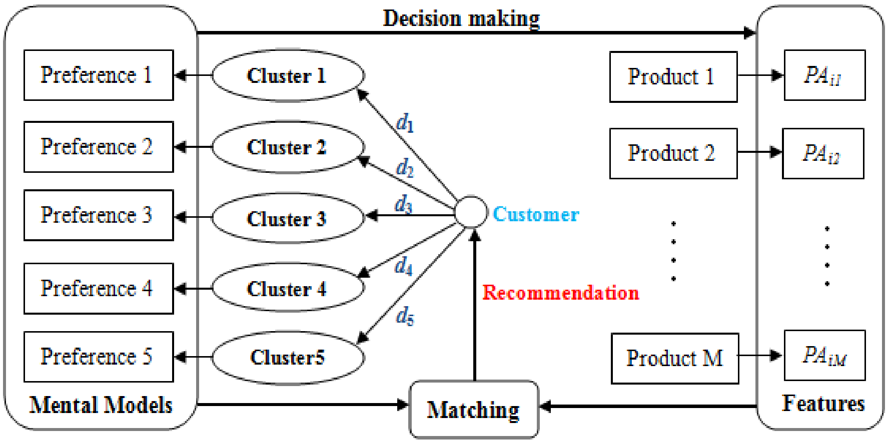

Fig. 6. Recommendation approach for new customer

New consumers' decision-making on Internet financial products should be affected by the preferences of closest clusters and have a shared mental model. Therefore, personalized recommendation is to find the products that best match the preferences of the above clusters. In order to achieve this purpose, we take the minimum cluster d_m as the closest cluster that the consumer is most likely to belong to, and introduce the following criteria function:

$$RK_j = \sum_{i=1}^{4} PA_{ic} * PA_{ij}, \; j = 1,2,3,\ldots,M. \tag{5}$$

Where, RK_j is the value of criterion function, PA_{ic} is the center values of the closest cluster, and PA_{ij} is the characteristic values of the product *j (j=1, 2, 3…,M)* considered to be recommended. RK_j is actually the weighted sum of PA_{ij} with coefficients PA_{ic}. The products are recommended according to the descending order of RK_j.

In order to test the performance of the above methods, we make recommendations to 11 new consumers from the actual financial products in the Chinese market. The physical products to be recommended include 12 banking products, 8 insurance products, 30 stocks and 22 futures, which are representative of the product features shown in Table 1. All consumers report that recommendations of our approach are more in line with their preferences than traditional approaches. Table 4 shows the comparison of consumers' averaged satisfactions between collaborative filtering approach (CFA) and our mental model approach (MMA) respectively.

Table 4. Comparison of the two approaches to the average satisfaction of consumers

Approach	Bank products	Insurance products	Stocks	Futures
CFA	83.1%	78.7%	71.1%	76.8%
MMA	92.6%	88.4%	79.2%	84.1%

Table 4 indicates that our proposed approach (MMA) can achieve about more than 8.7% of the average consumer satisfaction compared with the collaborative filtering method (CFA). However, factors such as the number of recommended products and the time effect of product profitability may affect the performance of recommended methods and consumers' satisfaction. For example, stocks and futures have more products than banking and insurance products, and their returns can be known in a very short time, which may lead to greater fluctuations in consumer satisfaction. Therefore, further rigorous testing and comprehensive analyses are needed to verify the performance of this method.

5. Summary and Discussion

Cognitive computing is an important development direction in the field of artificial intelligence, which involves the acquisition, calculation and expression of human complex cognitive characteristics. Under the background of consumer's decision-making of Internet financial products, this paper conducts the EEG-fNIRS experiment to study the above cognitive characteristics, and proposes a cognitive computing method based on neural activity data through BP-GA algorithm. The results show that it can achieve 87.6% to 92.3% accuracy in the computation of consumer's cognition of product convenience, profitability, liquidity and risk.

In addition, this paper also studies the characteristics of consumer mental model, and explores a new recommendation method based on its typical sharing mental model. The test results show that compared with the traditional method, this method is more in line with the preferences of consumers, and the average satisfaction is about 8.7% higher than collaborative filtering method.

This paper provides new ideas and methods for cognitive computing and Internet financial product recommendation. However, there are many problems that need further study. Future research can be carried out from the following aspects: first, accurate neural learning and prior knowledge utilization of human complex dynamic cognitive characteristics, as well as more effective computational methods; second, accurate description and classification of consumer mental model, and the improvement of the proposed recommendation approach.

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