# An Adaptive E-Commerce: Applying of Psychological Testing Method to Improve Buying Decision Process

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**ABSTRACT**

   In recent year, with the use of e-commerce sites the need for adaptive contents to help customers to find suitable online products to purchase. Despite the limited use of adaptive services, most of these sites have "complex buyer behavior" often marked by customer confusion and information overload because of neglecting customer purchasing power ability. Therefore, this paper applies psychological testing method called Computerized Adaptive Testing (CAT) taking into account product price, quality and customer ability (customer purchasing power). Whereas, the proposed system focuses on a new adaptivemechanism that gives the customer an opportunity to select best products from several categories on the basis of consumer perceptions (e.g. *perceivedquality* and *perceivedprice*). Experiment results show that applying CAT to E-Commerce can help and enhance buying decision process when searching for and selecting online products by providing suitable product quality and price with corresponding customer's ability.

**Keywords:**E-Commerce, Buyer Decision Processes, Computerized Adaptive Testing (CAT), RecommendedSystem**,** Customer Purchasing Power, Customer Decision Making.

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## تكييف التجارة الإلكترونية: تطبيق أسلوب الاختبارالنفسي لتحسين عملية قرار الشراء

**الخلاصة:**

في السنوات الأخيرة ،مع استخدام مواقع التجارة الإلكترونية تلك المواقع تحتاج ان تكيف محتوياتها لمساعدة العملاء في ا لعثورعلى المنتجات المناسبة للشراءعبرالإنترنت. على الرغم من الاستخدام المحدود لتلك الخدمات، معظم هذه المواقع لديها "سلوك المشتري المعقدة" غالبا ماتميزت في ارباك العملاء والتحميل الزائد للمعلومات بسبب إهمال القدرةالشرائية للعملاء. لذلك،هذاالبحث يضع طريقة اختبارالنفسي يسمى اختبارالتكيف المحوسب (CAT) مع الأخذ بنظرالاعتبارسعرالمنتج والجودة وقابلية العملاء (القوةالشرائيةللعملاء). في حين، يركز النظام المقترح على آلية جديدة للتكيف الذي يعطي العميل فرصة لاختيارأفضل المنتجات من قبل عدة فئات على أساس تصورات المستهلكين على سبيل المثالي نظرالجودة والسعر.اظهرت النتائج التجريبية باناستخدام اختبارالتكيف المحوسب في التجارة

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الإلكترونية يمكن أنت دعم وتحسن نوعية اتخاذ قرارات العميل عندالبحث واختيارالمنتجات عبرالإنترنت من خلال توفيرمنتجات ذات جودةعالية وبأسعارمناسبة لقدرة العميل الشرائية.

## INTRODUCTION

Buyer decision processes are the choice making methods embraced by customers with respect to a potential market exchange before, during, and after the buy of products. Although the models vary, there are five stages in the choice procedure issue(problem)/need-recognition, information search, evaluation of alternatives, purchase decision and post-purchase behavior. For product purchase, a customer needs a certain itemdoes not straight jump to purchase decision as right choice would be so perplexing [1]. All inexpert customers depend on which naive theory use (positive relationship between price and quality), a low cost can show low quality product, though a high value may infer superb product.While, expert customers depend on which knowledgeable theory uses (negative relationship between price and quality) a low price cannot be indicated as low quality product, whereas a high price cannot be implied as high quality product [2].Hoyer, Wayne D. Provideda perspective of choice making focused around the thought that customers are not spurred to participate in a  great deal of in-store decision making aside a few minutes of procurement when the item is acquired more than once and is moderately irrelevant [2]. Whereas, [3]investigated how distinctive online choice making procedures utilized by buyers impact the unpredictability of their internet shopping practices. Amid an online analysis, subjects were asked to perform a shopping assignment on a site offering item suggestions. Huge contrasts were seen between subjects' choice making techniques and their online shopping conduct.

The methodology buyers utilization to purchase items and services is diverse for each person and each classification of the item. However, they have been able to classify this behavior based on their level of association, and the degree of difference between the brands in the item category. Most of E-Commerce sites have "Complex Buyer Behavior" meanshigh participation with significant degrees of differences between the items[4]. However, this behavior often marked by customer confusion and information overload because of neglecting the customer purchasing power and interesting. Therefore, this paper proposes a novel approach to modify existing buyer decision stages start from information search and end with post-purchase behavior taking into account product price, quality, and customer purchasing power. Firstly, the proposed system evaluatescustomer purchasing power using CAT. Secondly, the proposed system recommends two lists of productsthroughout rankingof these lists from cheap to expensiveprice andfrom the high to the low quality depending on customer purchasing power and interesting.

## Related Work

Clients' choice making concerning the determination of items is one of the key issues in electronic marketing exploration. Nevertheless proficient service suppliers' impact on the buy choices for some items, these services still suffer from of lack of adaptation. Recommended frameworks are being utilized by a regularly expanding number of E-commerce destinations to help shoppers discover items to buy in order to create an adaptive environment called adaptive E-Commerce [5][6]. [7] Presents a clarification of (1) How recommended frameworks help E-commerce sites expand deal? (2) How does

recommendation agent use, recommendation agent characteristics, and different elements impact purchaser choice making methods and results? On the other hand, [8] displayed hybrid system of personalized product recommendation in e-commerce, by coordinating different strategies; every e-commerce client has relegated their own weights comparing to specific techniques.

Recommended frameworks that join data mining methods make their suggestions utilizing learning gained from the activities and properties of clients [9]. Moreover, data mining methods are progressively being utilized in both hybrid systems, to enhance the suggestions in beforehand fruitful applications, and in stand-alone recommended, to deliver exact proposals in already difficult spaces. The utilization of data mining algorithms has changed therecommendations types as applications move from recommending what to consume to also recommending when to consume [10]. Anadaptive e-commerce decision support system is proposed for electronic shopping in Jordan. Electronic retailers are supposed to use the proposed model in order to select perceived suitable delivery operating system [11].However, the researchertries to build the personalization in the client and the server using mobile agent to improve the speed and efficiency of search in producing a technique, crawling, that technique involve the previous user searches in databases and cookies, then if the user try to make a search on other time the proposed system produces to use all the first search results and the latest results from the world wide web [12]. Association rules based on genetic algorithm are intuitive, and as a powerful tool that have been used applied to collaborate e-commerce recommender systems [13].

Prior researches have focused basically on modifying and assessing diverse fundamental algorithms that create recommendations. Generally, most prior researches consider costumer inclination, hobbies, and browsing behaviors in adaptive systems. However, customer purchasing power typically is dismissed as an essential element in implementing adaptive techniques. Furthermore, an excess of hyperlink structuresin E-Commerce systems put an expansive data trouble on customers. This research will focus on a new adaptivemechanism that gives the customer an opportunity to select best products from several categories on the basis of consumer perceptions (e.g. *Perceivedquality* and *perceivedprice*).

## The Proposed SystemArchitectural

Figure 1 illustrates an adaptive approach for the proposed system, which includes eight stages of buying decision process and two databases; all steps of buying decision process areexplained below:

1.     **Step 1:** The problem or need recognition stage is the first and most critical venture in the proposed system. If there is no need, there is no purchase. The needs are related to features or the product specifications, or related to a desire for integration and belongings in the social environment.

2.     **Step 2:** Once the online consumer's need is identified, online consumer seeks information about possible solutions to the problem. Then the online consumer will seek an information to make his the online consumer opinion guides him/ her choice depends on an internal information comes from previous online experiences or depends on external information comes from other expert consumers.

3.        **Step 3:**  At this stage, the consumer feedback stage collects responses from online consumer using multi choice questions in order to estimate consumer purchasing power.

4.        **Step 4:** After the proposed system collects online consumer responses, the system estimates consumer's purchasing power, and then this valueis saved into consumer profile database.

5.        **Step 5:** after step 4, the proposed system will save the estimated consumer's purchasing power and experience into the customer profile database.

6.        **Step 6:**the proposed system will sendboth online consumer perceptions and evaluated consumer purchasing power to evaluate productquality.

7.        **Step 7:** the proposed system also sendsboth online consumer perceptions and evaluated consumer purchasing power to evaluate products perceived price.

8.        **Step 8:**the evaluated product quality receives customer information from the customer profile database.

9.        **Step 9:** the evaluated product quality also receives customer information from the customer profile database.

10.       **Step 10:** This is the first part of fifth stage called evaluationof alternatives according to the best perceived product quality, whereasthe proposed system evaluates products from the product database with best product quality using both online consumer perceptions and evaluated consumer purchasing power.

11.       **Step 11:** This is the second part of fifth stage called evaluationof alternatives according to the best perceived price, whenthe proposed system evaluates products from the product database with best perceived price using both online consumer perceptions and evaluated consumer purchasing power.

12.       **Step 12:** The system ranks the online products using product perceived price (e.g. Low price to highest price).

13.       **Step 13:** The system ranks the online products using product perceived quality (e.g. High quality to the low quality).

14.       **Step 14:**The system provides adaptive product with perceived quality closer to the consumer perceptions.

15.       **Step 15:**The system also provides an adaptive product with a perceived price closer to the consumer purchasing power.

16.       **Step 16:** This is the final stage, where the purchase happiness; clients' contrast online items and their desires then either fulfilled or disappointed? After that, a client will spread either negative or positive feedback about the item. At this stage, E-Commerce sites ought to precisely make positive post-purchase correspondence to captivate the clients.
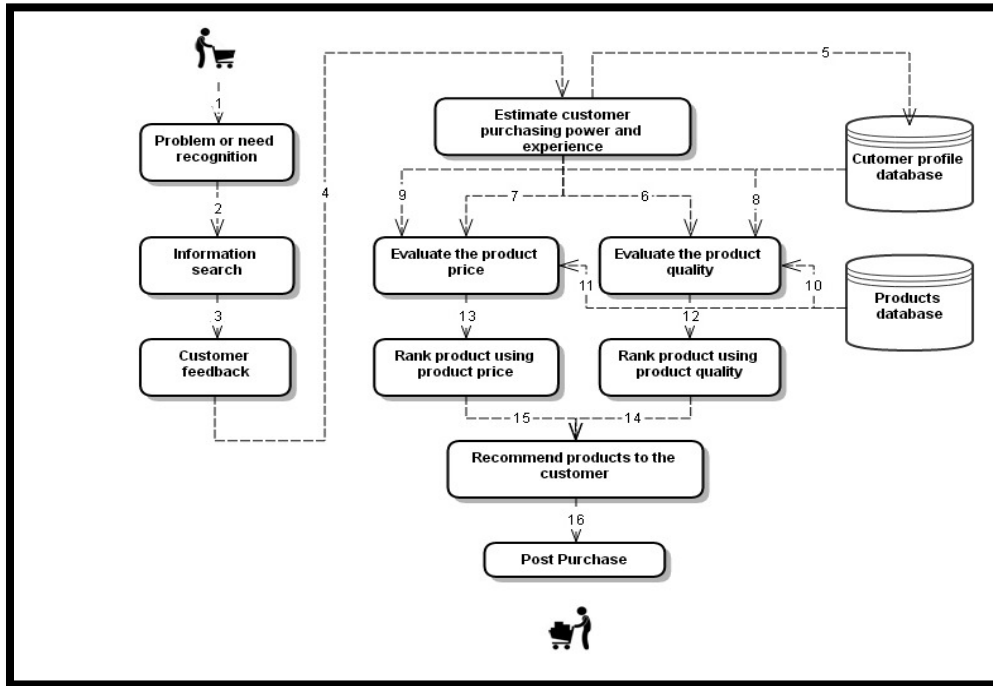
**Figure (1): An Adaptive E-Commerce.**

## Tuning Perceived Price and Quality of Products

To provide appropriate online products to customers based on their individual requirements, the CAT with a single parameter either *price* or *quality* are used to model an online product. The proposed system considers both customer perceptions (e.g. *Perceived quality* and *price*) and customer purchasing powerbecause these variables affect customer interests.

The most e-marketing sites, customers experience allow them to determine the *price* or *quality* parameters of products. However, this manner is not appropriate because most customers are not experts. Therefore, the proposed system automatically adjusts these parameters based on the psychometric scale considers both expert and inexpert customers.

**Definition 1:** (Product price levels). Assume that *P*= {*P1*, *P2*, *P3*} is the set of product price levels which incorporates three separate levels. Where *P1*denotesthe high priceevaluated as 3; *P2*denotesa moderate priceevaluated as 0; *P3*denotesthe low priceevaluated as -3.

**Definition 2:** (Product quality levels). Assume that *Q*= {*Q1*, *Q2*, *Q3*} is the set of product quality levels which incorporates three separate levels. Where *Q1*denoteslow quality, evaluated as -3; *Q2*denotesmoderate quality, evaluated as 0; *Q3*denoteshigh quality evaluated as 3.

**Definition 3:** (Average price and quality of the *Jth* itemusing customer community voting).

$$Price_j(voting) = \sum_{i=1}^{3} \frac{nij}{Nj} Pi, \quad Quality_j(voting) = \sum_{i=1}^{3} \frac{nij}{Nj} Qi \qquad \text{.... (1)}$$

When
$Price_j(voting)$and $Quality_j(voting)$Denote the average price and quality, respectively, of the *get*the product after customers give collaborative voting, *nij* represents the number of customers that giveinputs(feedback responses)associatingto the *ith*  price or quality levels for the *jth* product, *Nj* is the aggregate number of customers that rate the *jth* product.
   Furthermore, the adjusted price and quality of the product is a linear combination of the products as characterized by expert /inexpert customers, with an alternate weight allocated to each..

$$Price_j(adjusted) =$$
$$weight \times Price_j(expert) + (1 - weight) \times Price_j(voting) \qquad \text{...(2)}$$

$$Quality_j(adjusted) =$$
$$weight \times Quality_j(expert) + (1 - weight) \times Quality_j(voting) \qquad \text{...(3)}$$

**Evaluation of Customer Purchasing Power**
   A randomly chosen customer multi responses to a set of n online products is assumed. Online product selection in multi responses CAT is mainly based on Fisher Information [14].  For a single product, Fisher's Information function is defined by:

$$I_{ik}(\emptyset) = a_i^2 [\sum_{k=1}^{m} k^2 P_{ik}(\emptyset) - (\sum_{k=1}^{m} k^2 P_{ik}(\emptyset))^2] \qquad \text{... (4)}$$

Where
 *m* is the number of categories quantified by 3 and $P_{ik}(\emptyset)$is the probability that a customer with purchasing power $\emptyset$will end up in category *k* of product *i* .

$$P_{ik}(\emptyset) = \frac{e^{\sum_{v=0}^{k} a(\emptyset - bv)}}{\sum_{c=0}^{m} e^{\sum_{v=0}^{C} a(\emptyset - bv)}} \qquad \text{.... (5)}$$

Where
*a* is the slope parameter,  $b_v$is a product category parameter either $Price_j(adjusted)$ or $Quality_j(adjusted)$, $k$ ={0,1,2} is a category number represents {*low*, *moderate*, *high*} for a price and quality, respectively. When Fisher Information is used, the product is selected with maximum value of the information function at the estimated purchasing power level of the customer $i = \arg\max I_{ik}(\emptyset)$

**Evaluation of Alternatives**

After the customer feedback model re-evaluates customer purchasing power, the proposed system can recommend an online product to customers using the new purchasing power as adjusted by the feedback stage. Equation 4 is utilized to evaluate the matching degree for recommending suitable products to the costumer.

Ultimately, in this stage the proposed system can advise a list of online products to customers corresponding to purchasing power, according to the ranking order of information fisher value. Thus, the system provides two recommended lists to the customer; the first list is ranked from the best for  the worst price and the second one is ranked from the high to the low quality depending on customer purchasing power and interesting.

A product with a maximum fisher value under customer with specific purchasing power shows that the system introduced  here gives the mostnoteworthy recommendation need.

**Experimental Environment**

The proposed frameworkwas successfully implemented in Microsoft Windows 7 Ultimate using Apache Web server. The front-end script language PHP version 5.3.0 andMySQL  server  version 4.1.13are  utilized  to  executethe  proposed  system. Figure2shows the graphical format of the customer interface. The left frame is divided into two parts: the top part displays the product categories(e.g. Business phone, fun phone, lifestyle phone, etc.) and the bottom part displays a list of product manufactures (e.g. APPLE, HTC, SAMSUNG, etc.).

When a customer clicks on a product manufacture and then clicks on product category, the selected productcontent will be presented in the middle web pagein which it contains product specification and price. The bottom-middle window presents the feedback interface.

The proposed system gets the client's input through the criticism interface as answers to four predefined surveys as appeared:

1.      How do think about the price of the product?
2.      How do think about the quality of the product?
3.      Do you feel that the product price is appropriate for you?
4.      Do you feel that the product quality is appropriate for you?

Presently, under the product category, ''mobile-lifestyle phone'', the proposed system includes 18 lifestyle phones with different manufacturers. Moreover, each phone has a corresponding price and quality parameters, initially determined by an expert customer and each inexpert customer has a different purchasing power in working through each product unit initially quantified as "0" for all inexpert customers.

**Figure (2): Customer Interface**

## Experimental Results and Analysis

To analyze the results correctly, only 18 of phone products have been taken in this research (that's means this research can recommend products regardless of the size of samples using second experiment). Moreover, the proposed system illustrates two experiments: The first, the system will eliminate the recommended product from the recommended list of products after the customer experiences the recommended product, However, this method is inefficient if the number of products quite a few exactly, because the system provides unsuitable product to the customer as shown in table 1. Therefore, the second experiment is more efficient than the first one, even the number of product quite small as shown in table 2.

Table1 depicts a first experiment of a phone product recommendation using a customer's purchasing powerbased on the feedback gave by the inexpert customer. The product title indicates the subject of the product such as "Apple iPhone 5C 16GB"; thePVV denotes Perceived Price Value of product gave by both expert and inexpert customers, according to the Feedback Value FV field, and CPP field denotes Customer Purchasing Power initially quantified as "0" for all inexpert customers. The Max-IFV value denotes *Fisher's InformationValue* by using equation 4. The last field specifies the recommendation link of the corresponding product that closer to customer purchasing power.

**Table (1): An example of an elimination online recommended product based on costumer purchasing power.**

| Category | Product title | PVV | CPP | FV | Max-IFV | Recommended Product |
|---|---|---|---|---|---|---|
| **Phone** | - | - | 0.000 | | 0.421 | Voice Xtreme X5 |
| **Phone** | Voice Xtreme X5 | 0.2143 | 0.214 | 1 | 0.423 | Qmobile Noir Quatro Z5 |
| **Phone** | Qmobile Noir Quatro Z5 | 0.4286 | 0.321 | 1 | 0.423 | Huawei Ascend P7 |
| **Phone** | Huawei Ascend P7 | 0.4286 | 0.350 | 1 | 0.423 | Apple iphone 5C 16GB |
| **Phone** | Apple iphone 5C 16GB | 0.6429 | 1.030 | 2 | 0.423 | Samsung Galaxy S5 |
| **Phone** | Samsung Galaxy S5 | 1.0714 | 0.556 | 0 | 0.423 | Apple iphone 5 16GB |
| **Phone** | Apple iphone 5 16GB | 1.0714 | 0.240 | 0 | 0.423 | Samsung Galaxy S3 Neo |
| **Phone** | Samsung Galaxy S3 Neo | -0.428 | 0.142 | 1 | 0.422 | Haier W919 |
| **Phone** | Haier W919 | -0.642 | 0.041 | 1 | 0.420 | LG G3 |
| **Phone** | LG G3 | 0.2261 | -0.020 | 1 | 0.419 | Sony Xperia Z2 |
| **Phone** | Sony Xperia Z2 | 1.0714 | -0.150 | 0 | 0.419 | Apple iphone 5S 16GB |
| **Phone** | Apple iphone 5S 16GB | -1.5000 | -0.048 | 2 | 0.419 | Apple iphone 5 64GB |
| **Phone** | Apple iphone 5 64GB | 1.2857 | -0.144 | 0 | 0.419 | Voice Xtreme V90 |
| **Phone** | Voice Xtreme V90 | -1.500 | -0.055 | 2 | 0.419 | GFive President G10 Octa Core |
| **Phone** | GFive President G10 Octa Core | 1.2857 | -0.140 | 0 | 0.419 | Qmobile Noir i12 |
| **Phone** | Qmobile Noir i12 | -1.5000 | -0.060 | 2 | 0.421 | Nokia Lumia 630 Dual SIM |
| **Phone** | Nokia Lumia 630 Dual SIM | -1.7143 | 0.000 | 2 | 0.421 | HTC One M8 |
| **Phone** | HTC One M8 | 1.7143 | -0.033 | 1 | - | - |

Table 2 depicts a second experiment of a phone product recommendation based on a customer's purchasing power, according to the feedback gave by the inexpert customer.

Whereas, this experiment recommends suitable phone to the customer according to customer purchasing power.

**Table (2): An example of online product recommendation based on costumer purchasing power.**

| Category | Product title | PVV | CPP | FV | Max-IFV | Recommended Product |
|----------|---------------|-----|-----|----|---------|--------------------|
| Phone | - | - | 0.000 | - | 0.4212 | Voice Xtreme X5 |
| Phone | Voice Xtreme X5 | 0.214 | 0.214 | 1 | 0.4238 | Voice Xtreme X5 |
| Phone | Voice Xtreme X5 | 0.214 | 0.321 | 1 | 0.4232 | Voice Xtreme X5 |
| Phone | Voice Xtreme X5 | 0.428 | 0.357 | 1 | 0.4235 | Qmobile Noir Quatro Z5 |
| Phone | Qmobile Noir Quatro Z5 | 0.428 | 1.030 | 2 | 0.4237 | Qmobile Noir Quatro Z5 |
| Phone | Qmobile Noir Quatro Z5 | 1.071 | 0.556 | 0 | 0.4234 | Sony Xperia Z2 |
| Phone | Sony Xperia Z2 | 0.642 | 0.240 | 0 | 0.4238 | Apple iphone 5C 16GB |
| Phone | Apple iphone 5C 16GB | 0.214 | 0.142 | 1 | 0.4235 | Voice Xtreme X5 |
| Phone | Voice Xtreme X5 | 0.214 | 0.041 | 1 | 0.4221 | Voice Xtreme X5 |
| Phone | Voice Xtreme X5 | 0.214 | -0.020 | 1 | 0.4207 | Voice Xtreme X5 |
| Phone | Voice Xtreme X5 | 0.214 | -0.150 | 0 | 0.4194 | Voice Xtreme X5 |
| Phone | Voice Xtreme X5 | -0.428 | -0.048 | 2 | 0.4199 | Samsung Galaxy S3 Neo |
| Phone | Samsung Galaxy S3 Neo | 0.214 | -0.144 | 0 | 0.4192 | Voice Xtreme X5 |
| Phone | Voice Xtreme X5 | -0.428 | -0.055 | 2 | 0.4197 | Samsung Galaxy S3 Neo |
| Phone | Samsung Galaxy S3 Neo | 0.214 | -0.140 | 0 | 0.4191 | Voice Xtreme X5 |
| Phone | Voice Xtreme X5 | -0.428 | -0.060 | 2 | 0.4195 | Samsung Galaxy S3 Neo |
| Phone | Samsung Galaxy S3 Neo | 0.214 | -4E-4 | 2 | 0.4212 | Voice Xtreme X5 |
| Phone | Voice Xtreme X5 | 0.214 | -0.033 | 1 | 0.4212 | Voice Xtreme X5 |

The purchasing power of customers can be rapidly re-assessed according to customerfeedback who have experienced the advised phones. Means, the adjusted purchasing power of customers is increased/ reduced using  the customers' feedback. According CAT, a customer's purchasing power is increased if all of the content of the recommended products is suitable price or quality to the customer. The customer's

purchasing power will be reduced if the content of the recommended products is unsuitable price or quality to the customer.Figure 3 displays the relationship between the customer purchasing power to the perceived price parameter of the advisedproduct based onthe second method. The perceived price parameter of the advised product is strongly matched with customer purchasing power.

Furthermore, to investigate the significant differences between perceived price (B Sample) and purchasing power (C sample), a Paired t-Test can be used inthe experiment (2) as shown in the following results:

```
Data   Mean  Variance      N
-------------------------------------------------
B       0.202390.1322118
C       0.124950.0894218
-------------------------------------------------
t = 1.72019
p = 0.10355
```

As mentioned in the above results where **N** is a number of phone products equal to **18**,*t* is the value of the paired **t-Test** which is calculated by dividing means of sample on standard deviation. Furthermore,*p* is the value of**p-value**equal **0.10355.** For example, the mean and variance of sample **B** equal to **0.20239** and **0.13221.** At the **0.05** level,the two means are NOT significantly different.
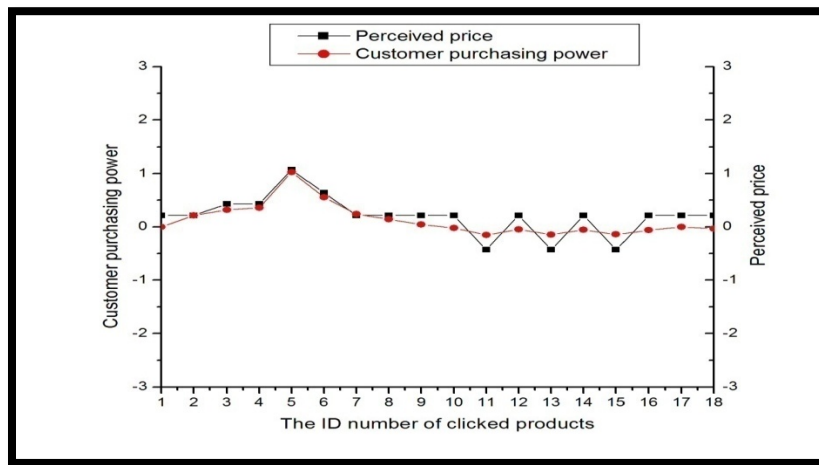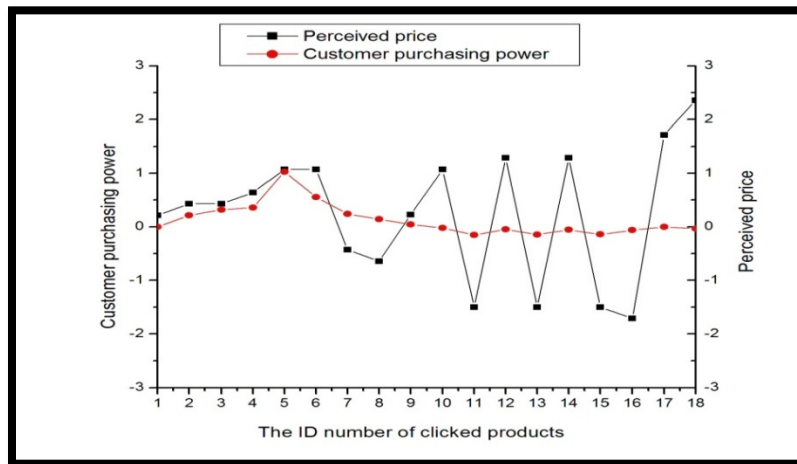


**Figure (3): the relationship between the customer purchasing power to the perceived price parameter of the advised product.**

However, Figure 4 also displays the relationship between the customer purchasing power to the perceived price parameter of the advisedproduct based on the first method. The perceived price parameter of the advisedproduct is weakly matchingwith customer purchasing power. A Paired t-Test can be used inthe experiment (1) as shown in the following results:

**Data    Mean  Variance        N**

---------------------------------------------------------------
**B       0.250651.4869  18**
**C       0.124950.0894218**

---------------------------------------------------------------
**t = 0.45919**
**p = 0.65191**

As mentioned in the above results where **N** is a number of phone products equal to **18**,*t* is the value of paired **t-Test** which is calculated by dividing means of sample on standard deviation. Furthermore, *p* is the value of **p-value**equal **0.65191**. For example, the mean and variance of sample **B** equal to **0.25065** and **1.4869.** At the **0.05** level, the two means are NOT significantly different.



**Figure(4): the relationship between the customer purchasing power to the perceived price parameter of the advised product.**

**Conclusion**

This research proposed an adaptive E-Commerce by applying of psychological testing method called CAT to improve buying decision process, which evaluate the purchasing power of online customers and recommends appropriate products to the customer. Using CAT provides an adaptive E-Commerce according to online products experiences of customers and their responses. Furthermore, perceived price and quality can be naturally balanced utilizing the collaborative voting methodologies. Exploratory results demonstrate that the proposed system can definitely giveadaptive products based on customer purchasing powers, and moreover can improve buying decision process and effectiveness.

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