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

Dr. Ayad R. Abbas
Computers Science Department, University of Technology/Baghdad.
Email: ayad_cs@yahoo.com

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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. perceived quality and perceived price). 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.

تكيف التجارة الإلكترونية: تطبيق أساليب الاختيار النفسي لتحسين عملية قرار الشراء

الخلاصة:
في السنوات الأخيرة مع استخدام مواقع التجارة الإلكترونية تلك المواقع تحتاج أن تكيف محتوياتها لمساعدة العملاء في اكتشاف المنتج المناسب للشراء عبر الإنترنت. على الرغم من الاستخدام المحدود لتلك الخدمات، معظم هذه المواقع لديها "سلوك المشتري المعقد" غالباً ما يتميز في أرباك العميل والتكيف الزائد للمعلومات بسبب إهمال القدرة الشرائية للعملاء. لذلك، هذا البحث يضع طريقة اختبار النموذج يسمى اختبار النموذج الموحد (CAT) (Computerized Adaptive Testing). في حين، يركز النظام المتنقل على آلية جديد لاختبار الذي يعطي الفرد فرصة لاختيار أفضل المنتجات من قبل المادة على أساس تصورات المستهلكين على سبيل المثال، نظر الأجهزة والمعرفة، أظهرت النتائج التجريبية بالاستخدام لاختبار النموذج الموحد في التجارة

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2412-0758/University of Technology-Iraq, Baghdad, Iraq
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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 item does 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. Provided a 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” mean high 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 evaluates customer purchasing power using CAT. Secondly, the proposed system recommends two lists of product throughout ranking of these lists from cheap to expensive price and from 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]. An adaptive 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 researcher tries 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 structures in 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 System Architectural

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 are explained 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 value is 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 send both online consumer perceptions and evaluated consumer purchasing power to evaluate product quality.
7. **Step 7:** The proposed system also sends both 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 evaluation of alternatives according to the best perceived product quality, whereas the 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 evaluation of alternatives according to the best perceived price, when the 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.
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 power because 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 \( P = \{P_1, P_2, P_3\} \) is the set of product price levels which incorporates three separate levels. Where \( P_1 \) denotes the high price evaluated as 3; \( P_2 \) denotes a moderate price evaluated as 0; \( P_3 \) denotes the low price evaluated as -3.

**Definition 2:** (Product quality levels). Assume that \( Q = \{Q_1, Q_2, Q_3\} \) is the set of product quality levels which incorporates three separate levels. Where \( Q_1 \) denotes low quality, evaluated as -3; \( Q_2 \) denotes moderate quality, evaluated as 0; \( Q_3 \) denotes high quality evaluated as 3.
Definition 3: (Average price and quality of the Jth item using customer community voting).

\[ \text{Price}_j(\text{voting}) = \sum_{i=1}^{3} \frac{n_{ij}}{N_j} P_i, \quad \text{Quality}_j(\text{voting}) = \sum_{i=1}^{3} \frac{n_{ij}}{N_j} Q_i \quad \ldots (1) \]

When \( \text{Price}_j(\text{voting}) \) and \( \text{Quality}_j(\text{voting}) \) denote the average price and quality, respectively, of the product after customers give collaborative voting, \( n_{ij} \) represents the number of customers that give inputs (feedback responses) associating to the \( i \)th price or quality levels for the \( j \)th product, \( N_j \) is the aggregate number of customers that rate the \( j \)th 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.

\[ \text{Price}_j(\text{adjusted}) = \text{weight} \times \text{Price}_j(\text{expert}) + (1 - \text{weight}) \times \text{Price}_j(\text{voting}) \quad \ldots (2) \]

\[ \text{Quality}_j(\text{adjusted}) = \text{weight} \times \text{Quality}_j(\text{expert}) + (1 - \text{weight}) \times \text{Quality}_j(\text{voting}) \quad \ldots (3) \]

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:

\[ I_{ik}(\emptyset) = a_i^2 \left[ \sum_{k=1}^{m} k^2 P_{ik}(\emptyset) - \left( \sum_{k=1}^{m} k^2 P_{ik}(\emptyset) \right)^2 \right] \quad \ldots (4) \]

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 \( i \).

\[ P_{ik}(\emptyset) = \frac{\sum_{\beta=0}^{k} e^{\alpha - b_{ik}}}{\sum_{\alpha=0}^{m} e^{\alpha - b_{ik}}} \quad \ldots (5) \]

Where \( a \) is the slope parameter, \( b_{ik} \) is a product category parameter either \( \text{Price}_j(\text{adjusted}) \) or \( \text{Quality}_j(\text{adjusted}), k = \{0, 1, 2\} \) 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 customer. 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 most noteworthy recommendation need.

Experimental Environment

The proposed framework was successfully implemented in Microsoft Windows 7 Ultimate using Apache Web server. The front-end script language PHP version 5.3.0 and MySQL server version 4.1.13 are utilized to execute the proposed system. Figure 2 shows 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 manufacturers (e.g., APPLE, HTC, SAMSUNG, etc.).

When a customer clicks on a product manufacture and then clicks on product category, the selected product content will be presented in the middle web page in 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.
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.

Table 1 depicts a first experiment of a phone product recommendation using a customer’s purchasing power based on the feedback gave by the inexpert customer. The product title indicates the subject of the product such as “Apple iPhone 5C 16GB”; the PVV 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 Information Value 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 customer purchasing power.

<table>
<thead>
<tr>
<th>Category</th>
<th>Product title</th>
<th>PVV</th>
<th>CPP</th>
<th>FV</th>
<th>Max-IFV</th>
<th>Recommended Product</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phone</td>
<td>-</td>
<td>-</td>
<td>0.000</td>
<td>0.421</td>
<td>Voice Xtreme X5</td>
<td></td>
</tr>
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<td>0.423</td>
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</tr>
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<td>0.423</td>
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</tr>
<tr>
<td>Phone</td>
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<td>0.350</td>
<td>1</td>
<td>0.423</td>
<td>Apple iphone 5C 16GB</td>
</tr>
<tr>
<td>Phone</td>
<td>Apple iphone 5C 16GB</td>
<td>0.6429</td>
<td>1.030</td>
<td>2</td>
<td>0.423</td>
<td>Samsung Galaxy S5</td>
</tr>
<tr>
<td>Phone</td>
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<td>1.0714</td>
<td>0.556</td>
<td>0</td>
<td>0.423</td>
<td>Apple iphone 5 16GB</td>
</tr>
<tr>
<td>Phone</td>
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<td>1.0714</td>
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<td>0.423</td>
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<td>1</td>
<td>0.422</td>
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<td>0.419</td>
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<td>0.419</td>
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</tr>
<tr>
<td>Phone</td>
<td>Apple iphone 5S 16GB</td>
<td>-1.5000</td>
<td>-0.048</td>
<td>2</td>
<td>0.419</td>
<td>Apple iphone 5 64GB</td>
</tr>
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<td>Phone</td>
<td>Apple iphone 5 64GB</td>
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<td>-0.033</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

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 customer purchasing power.

<table>
<thead>
<tr>
<th>Category</th>
<th>Product title</th>
<th>PVV</th>
<th>CPP</th>
<th>FV</th>
<th>Max-IFV</th>
<th>Recommended Product</th>
</tr>
</thead>
<tbody>
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<td>Voice Xtreme X5</td>
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</tr>
</tbody>
</table>

The purchasing power of customers can be rapidly re-assessed according to customer feedback 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 advised product based on the 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 in the experiment (2) as shown in the following results:

<table>
<thead>
<tr>
<th>Data</th>
<th>Mean</th>
<th>Variance</th>
<th>N</th>
</tr>
</thead>
<tbody>
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<td>0.20239</td>
<td>0.1322118</td>
<td>18</td>
</tr>
<tr>
<td>C</td>
<td>0.12495</td>
<td>0.0894218</td>
<td>18</td>
</tr>
</tbody>
</table>

\[ t = 1.72019 \]
\[ p = 0.10355 \]

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.

However, Figure 4 also displays the relationship between the customer purchasing power to the perceived price parameter of the advised product based on the first method. The perceived price parameter of the advised product is weakly matching with customer purchasing power. A Paired t-Test can be used in the experiment (1) as shown in the following results:
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 give adaptive products based on customer purchasing powers, and moreover can improve buying decision process and effectiveness.
REFERENCES