

A Fuzzy Logic Based Personalized Recommender System

Ojokoh, B. A., Omisore, M. O, Samuel, O. W, and Ogunniyi, T. O.

Department of Computer Science
Federal University of Technology
Akure, Nigeria.

Abstract—The ever-increasing number of E-commerce sites on the Internet has brought about information overload. This has made it difficult for consumers of certain products to find information about such products in an attempt to purchase products that best satisfies them. It has equally reduced the volume of product sales in the E-commerce domain. Hence, this paper proposes a personalized recommender system driven by fuzzy logic technique. The proposed system intelligently mines information about the features of laptop computers and provides professional services to potential buyers by recommending optimal products based on their personal needs. Fuzzy Near Compactness (FNC) concept is employed to measure the similarity between consumer needs and product features in order to recommend optimal products to potential buyers.

Experimental result of the proposed system with 50 laptop computers consisting of Acer, Dell, HP, Sony, and Toshiba proves its effectiveness.

Keywords-Fuzzy logic; Laptops; Recommendation system; Attributes; E-Commerce; Mining.

I. INTRODUCTION

The incessant growth of the Web has led to rapid expansion of e-commerce among other things. The large amount of product information on the Web poses great challenges to both customers and online businesses. More customers are turning towards online shopping because it is relatively convenient, reliable, and fast; yet such customers usually experience difficulty in searching for products on the Web due to information overload. Online businesses have often been overwhelmed by the rich data they have collected and find it difficult to promote products appropriate to specific customers. There is also the problem of ineffective utilization of the available large amount of product information from online transactions to support better decision making by both buyers and sellers [1]. To address these information overload problems, e-commerce stores are now applying mass customization principles not to the products but to their presentation in the on-line store [24]. One way to achieve mass customization in e-commerce is the use of recommender systems [3].

Recommender systems are used by an ever-increasing number of E-commerce sites to help consumers find products that best suit their needs [3]. Typically, a recommender system analyzes

data about items, or interactions between users and items in order to find associations between items and users. It provides advice to users about items they might wish to purchase or examine. The recommendations made by such a system can help users navigate through large information spaces of product descriptions, news articles or other items [1][2]. Various factors are considered when recommending products to online buyers; these include: top sellers of a particular product, demographic information of buyers, and analysis of the past buying behavior of customers to predict their buying behaviors in the future. These forms of recommendation include suggesting products to the consumer, providing personalized product information, summarizing community opinions, and providing community critiques.

Personalized recommendation systems enable consumers to easily access information about products they are interested in, and save time of reading through electronic documents. Moreover, enterprises can get to know customers' buying behaviors better, and develop efficient marketing strategies to attract different customers. Customer's satisfaction, and loyalty can thus be increased; the increase in the visiting frequency of customers can further create more transaction opportunities and benefit the Internet enterprises [12]. A good personalized recommendation system should be able to improve user satisfaction; a key attribute to customer loyalty and continued use [19].

This research proposes a fuzzy-logic based personalized recommender system for products that are not frequently purchased such as laptop computers. The proposed system is not only aimed at recommending optimal products to prospective buyers, but also, at promoting the rate at which customers visit online stores and eventually increase sales for online businesses. Specially, we empirically evaluate the superiority of the proposed system in a controlled experiment with 50 laptop computers consisting of Acer, Dell, HP, Sony, and Toshiba. The outcome of the experiment shows that the proposed system induces greater user satisfaction. In turn, this study demonstrates

the viability and desirability of personalized recommendation systems for customers' product selections.

The remainder of this paper is organized as follows: Section II discusses the research background and related works. Section III presents the architecture of the proposed system and method adopted by the research. Section IV presents the experimental result and evaluation of the proposed system, while Section V presents the conclusion and recommendations.

II. BACKGROUND OF STUDY

A review of recommendation systems and fuzzy logic concept is presented in this section.

A. Recommender Systems

A recommender system can be described as one that gives suggestions and recommendations to users when they are making a decision while faced with different choices. [12] describe a recommender system as a system which can acquire users' opinions about different items and also use these opinions to direct users to those items that might be interesting to them. [13] presents a recommender system as one that predicts what items a user might find interesting or suitable to his or her needs. [14] defines a recommender system in terms of personalization, as any system that can produce individualized recommendations and have the ability to guide users in a personalized manner to find interesting information on items in a large space of possible options. [3] [10] [12] discusses various classifications of recommendation techniques. [14] classifies recommendation techniques in terms of the underlying data used by the system as Collaborative filtering, Content-based, Demographic, Utility-based and Knowledge-based. Two broad classifications of recommendation techniques are Social-based and Information-based techniques. [10] view the taxonomy using two key dimensions: the degree of automation and the degree of persistence in the recommendations. They outlined the types of recommender systems as non-personalized, attribute-based, item-to-item correlation, and people-to-people (user-to-user) correlation. Further, [3] added raw retrieval, manually selected and statistical summarization to the list.

Personalization, a special form of differentiation, allows a website to respond to customers' unique and particular needs. The term 'personalization' is often used in the context of recommendation systems that selectively promote products to end-users based on the analysis of earlier interactions [10]. The five stages of personalization followed in this work are: collecting customer information, profiling customers, comparing similarity, delivering and presenting personalized information, and measuring customer responses.

Attribute-based recommender systems are the ones in which recommendations depend on the properties of the item in question [10]. Many of the personalized attribute-based works deal with recommendations involving similar items [11]. In this our proposed system, "personalized attribute-based" assumes a broader meaning. It involves storing and mining information

about each individual customer after supplying his/her preference and requirements information regarding a particular product. It also involves the mining of information about the attributes of the products, as obtained from experts via consultation.

B. Fuzzy Logic System

A Fuzzy Logic System (FLS) can be defined as the nonlinear mapping of an input data set to a scalar output data set [18]. Fuzzy sets have attracted growing attention and interest in modern information technology, production technique, decision making, pattern recognition, diagnostics and data analysis among others [20][21][22]. When a problem has dynamic behavior, fuzzy logic is a suitable tool that deals with such problem [23]. That is to say, fuzzy logic finds its strength in providing accurate solutions to problems that involve the manipulation of several variables. FLS consists of four main parts: The Fuzzifier, A Rule Base, An Inference Engine and A Defuzzifier. These components and the general architecture of a FLS are presented in Fig. 1.

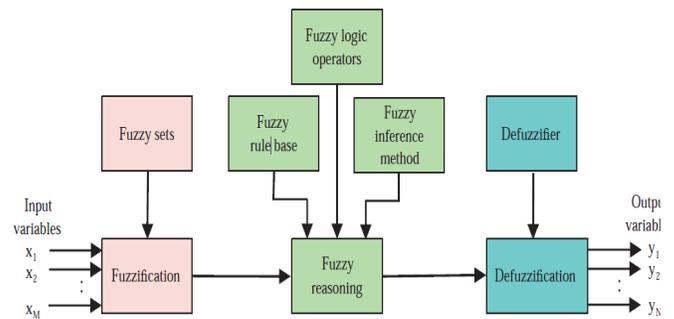


Figure 1. Architecture of FLS

A step by step procedure for implementing a FLS is given as follows. Firstly, a crisp set of input data are gathered and converted to a fuzzy set using fuzzy linguistic variables, fuzzy linguistic terms, and membership functions. This step is known as fuzzification. Afterwards, an inference is made based on a set of formulated rules. Lastly, the resulting fuzzy output is mapped to a crisp output using the output membership functions in the defuzzification step [18].

Our proposed system adopts the concept of Triangular Fuzzy Number (TFN) for expressing consumer needs and product features. A TFN is a particular case of fuzzy sets that has a triangular-shaped membership function which is often viewed as possibility distribution. Assuming that \tilde{C} is a TFN, then $\tilde{C} = (C_1, C_2, C_3)$ where $C_1, C_2,$ and C_3 are real numbers and $C_1 \leq C_2 \leq C_3$. The linguistic set presented in TABLE I are used to enable consumers express their opinion regarding their needs and as well for domain experts to easily evaluate features of laptop computers.

TABLE I. LINGUISTIC VARIABLES AND ASSOCIATED TFN

S /No.	Linguistic Term	TFN
1	Very Low (VL)	(0,1,2)
2	Low (L)	(1,2,3)

3	Medium Low (ML)	(2,3,4)
4	Medium (M)	(3,4,5)
5	Medium High (MH)	(4,5,6)
6	High (H)	(5,6,7)
7	Very High (VH)	(6,7,8)

Fig. 2 represents the corresponding membership function for the variables shown in TABLE I, and this shows the degree of membership of each class of linguistic term.

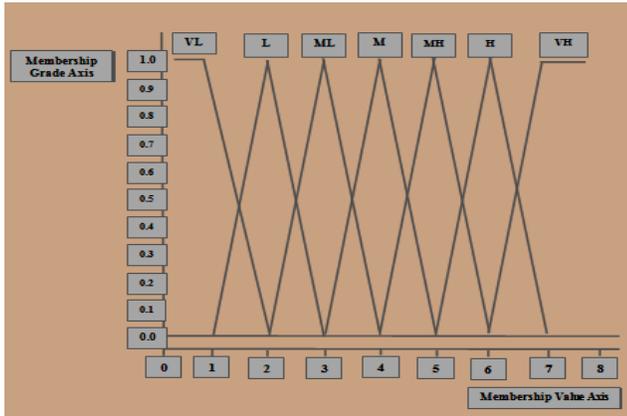


Figure 2: Membership Function of Input and Output Variables

III. SYSTEM ARCHITECTURE

The architecture of the proposed web-based personalized recommender system is presented in Fig. 3.

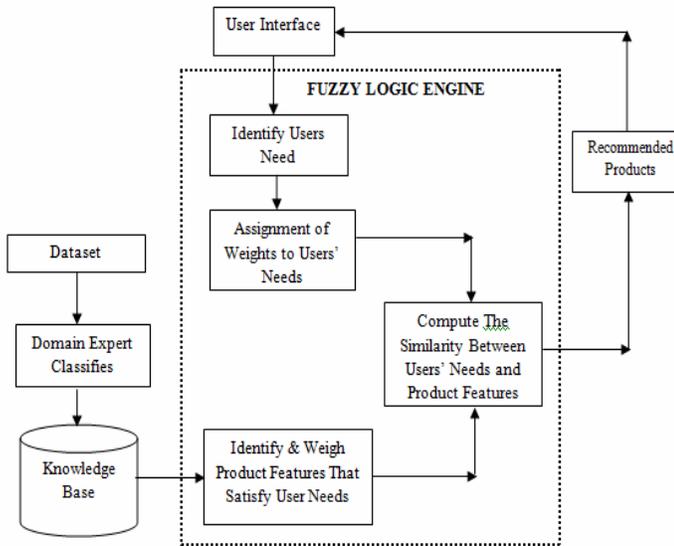


Figure 3: System Architecture

The customer supplies his needs in qualitative form via the user interface presented in Fig. 4 below. The system in turn transforms the needs to their respective quantitative forms using the concept of Fuzzy logic as explained in Section II above. This computation eventually produces a TFN which represents an aggregate of the consumer's needs. A set of computation is also carried out for all the laptop products in the database. The result of the computation for each laptop product is also a TFN. Finally, the system compares the TFN that represents the user's needs with the set of TFNs of the laptops and the five closest laptops to the user's needs are recommended to the user. The description of how the proposed system works is given in the remaining part of this section.

A. Identifying and Weighing Customer Needs

As part of steps to implement the proposed system, customers' needs are first identified. Usually, buyers of less frequently purchased products such as laptops do not have enough information to make adequate decision about the exact product to purchase, especially due to their, level of knowledge about the product domain. For instance, a perpetual graphic designer may find it relatively difficult to specify the speed and type of processor (CPU) that would efficiently satisfy his need, but it is much simpler to express his needs on the bases of qualitative attributes which could be mapped to the components of a laptop that support such needs. In order to obtain the needs of a consumer, we designed a user interface and it is represented in Fig. 4. The interface consists of well structured qualitative questions about the likely needs of consumers of laptop products and the extent to which they carry out the needs.

REQUIREMENT: NATURE OF LAPTOP COMPUTERS USAGE							
Home Use							
	Very Low	Low	Medium Low	Medium	Medium High	High	Very High
Downloading	<input type="radio"/>						
Listening to Music	<input type="radio"/>						
Playing Of Games	<input type="radio"/>						
Watching Movies	<input type="radio"/>						
Business Use							
Application Programming	<input type="radio"/>						
Word Processing	<input type="radio"/>						
Data Analysis/Mathematical Operations	<input type="radio"/>						
Graphics Handling	<input type="radio"/>						
Others							
Price Consideration	<input type="radio"/>						
Weight of Computer	<input type="radio"/>						
Battery Back up	<input type="radio"/>						
Screen Size	<input type="radio"/>						

Figure 4: Interface for Specifying User's Needs

Each consumer is expected to provide an answer to each question in Fig. 4 which represents a need based on his preference. The proposed method allows consumers to express their needs in qualitative form, converts such needs to their corresponding quantitative form using the concept of fuzzy logic, maps the values that represent the needs with the retrieved laptop products from the database, and finally recommends laptop products that best satisfy the consumer's needs.

The description of how consumer needs are being processed is given as follows. Since the quality of the critical components are the key factors that determine the capability of a laptop, each qualitative need of certain consumer is associated with a number of critical components of a laptop.

Assuming that the components of a laptop that support the i^{th} need of a consumer is represented by a vector \tilde{N}_i , and it is known as the Need Capability Vector (NCVec) and can be represented by equation (1) below.

$$\tilde{N}_i = (\tilde{c}_i^1, \tilde{c}_i^2, \dots, \tilde{c}_i^n) \quad (1)$$

where $\tilde{C}_i^j = (C_i^1, C_i^2, C_i^3)$ is a TFN and \tilde{C}_i^j represents the j^{th} component associated with the i^{th} consumer need, and $i = 1, \dots, m; j = 1, \dots, n$ For instance if $i = \text{downloading}$, then

$$\tilde{N}_{\text{downloading}} = (\tilde{C}_{\text{downloading}}^1, \tilde{C}_{\text{downloading}}^2, \dots, \tilde{C}_{\text{downloading}}^n)$$

Considering the fact that different components have different influences on the capability of a laptop in a certain customer need, an ability weight vector, $\tilde{V}_i = (V_i^1, V_i^2, \dots, V_i^n)$ is assigned to the Need capability vector in equation (1).

Hence, the Synthetical Capability Value for \tilde{N}_i is given by:

$$SCV\tilde{N}_i = (\tilde{C}_i^1 * V_i^1, \tilde{C}_i^2 * V_i^2, \dots, \tilde{C}_i^n * V_i^n) \quad (2)$$

Then, the cumulative sum of the TFNs of $SCV\tilde{N}_i$ for a particular consumer is computed as follows:

$$\begin{aligned} CumSCV\tilde{N}_m = & ((\tilde{C}_i^1 * V_i^1 + \tilde{C}_{i+1}^1 * V_{i+1}^1 + \dots + \tilde{C}_m^1 * V_m^1) + \\ & [\tilde{C}_i^2 * V_i^2 + \tilde{C}_{i+1}^2 * V_{i+1}^2 + \dots + \tilde{C}_m^2 * V_m^2] +, \dots, + \\ & [\tilde{C}_i^n * V_i^n + \tilde{C}_{i+1}^n * V_{i+1}^n + \dots + \tilde{C}_m^n * V_m^n]) \end{aligned} \quad (3)$$

and the final result of $CumSCV\tilde{N}_m$ is also a TFN.

B. Identifying and Weighing Laptop Attributes

Since the components of a laptop have different technical attributes, each component is represented by a vector of attribute functional values as given in equation (4) below.

$$\tilde{A}_i = (\tilde{A}_i^1, \tilde{A}_i^2, \dots, \tilde{A}_i^n) \quad (4)$$

where $\tilde{A}_i^j = (\tilde{A}_i^{j1}, \tilde{A}_i^{j2}, \tilde{A}_i^{j3})$ and is a TFN. i represent the i^{th} component of a laptop and j represents the j^{th} technical attribute of the component. $j = 1, 2, 3, \dots, n$. Because, different technical attribute have different influence on the capability of a

component, an attribute weight vector, $(w_i^1, w_i^2, \dots, w_i^n)$ is established and assigned to the technical attributes functional vectors in equation (4). Therefore, we proceed to compute the Component Capability Value of a component using equation (5) below:

$$P^k_i = \sum_{j=1}^n (\tilde{A}_i^{jk} * w_i^j) \quad (5)$$

and the result of this computation also gives a TFN that is:

$$\tilde{P}_i = (P_i^1, P_i^2, P_i^3)$$

where $A_i^{jk} \in \tilde{A}_i^j$ and $\tilde{P}_i^k \in \tilde{P}_i, k = 1, 2, 3$. The component capability vector $\tilde{P} = (\tilde{P}_1, \tilde{P}_2, \dots, \tilde{P}_n)$ is obtained for every component that makes up each laptop, and a cumulative value (CumP) is obtained for every brand of laptop computer found in the database by using equation (6) below:

$$CumP_k = (\tilde{P}_1^k + \tilde{P}_2^k + \dots + \tilde{P}_n^k) \quad (6)$$

Finally, a vector that represents the value for all laptop products in the database is obtained, and it is represented as shown below.

$$P_k = (CumP_1, CumP_2, CumP_3, \dots, CumP_n) \quad (7)$$

C. Mapping Consumers Needs With Product Attributes

The system then employs a technique which helps to identify the best laptop products that satisfies the needs of a consumer.

Having obtained P_k (equation 7) for all laptops in the database and $CumSCV\tilde{N}_m$ (equation 3) for each consumer needs, we proceed to compute the Euclidean fuzzy near compactness between $CumSCV\tilde{N}_m$ for the consumer needs with the earlier computed, P_k for all the laptops in the database to measure the similarity between consumer needs and laptop products.

Assuming $Cum\tilde{N}_m = (X^1_a, X^2_a, X^3_a)$ is a compared TFN while $\tilde{P}_i = (Y^1_b, Y^2_b, Y^3_b)$ is the target TFN, then the Euclidean fuzzy near compactness between $CumSCV\tilde{N}_m$ and \tilde{P}_i is defined in equation (8) as follows:

$$N_E(Cum\tilde{N}_m, \tilde{P}_i) = \frac{1}{\sqrt{3}} \left(\sum_{j=1}^3 |X^j_a - Y^j_b|^2 \right)^{1/2} \quad (8)$$

While the near compactness between $CumSCV\tilde{N}_m$ and \tilde{P}_i gets smaller, $CumSCV\tilde{N}_m$ is more similar to \tilde{P}_i . The same process is carried out for $\tilde{P}_i, i = 1, 2, \dots, n$. The proposed system then recommends the five closest laptop products to the consumer's needs.

IV. EXPERIMENT AND RESULTS

The proposed system could be applied to recommend less frequently purchased products and provide useful information for consumers of laptop computers. This system could also be suitably used to recommend other consumer electronic products, such as digital cameras, mobile phones and the likes. Therefore, this experiment concentrates on evaluating the proposed system's behavior with respect to recommending optimal products that suits the need of various consumers.

A. Data Set

A dataset of laptops features were gotten from CNET review center (<http://www.cnet.com>). The dataset contains 50 laptops of different brands including Acer, Dell, HP, Sony, and Toshiba. TABLE II below shows a sample of technical attributes and functional values of a selected laptop brand (Dell Inspiron 14Z). Laptop Computers are made up of different components comprising of varying technical attributes. In order to classify the laptops accordingly, three experts in the domain of Computer Engineering were consulted. The classification was done based on common criteria of different laptop computers. For instance, we classified the display attribute of a laptop computer with screen size between 12.1" and 13.7" as *Medium*, while a laptop with hard disk size in the range of 320GB and 500GB was classified as *Medium-High*, and so on.

TABLE II. THE TECHNICAL ATTRIBUTES OF DELL INSPIRON 14Z

Component	Technical Attribute(s)	Attribute Value	Functional Value
CPU	Frequency	2.0GHz	Medium
	Manufacturer	Intel	Very High
	FSB	667MHz	Medium High
	Type	Core i3	Medium High
	L2 Cache Size	2000KB	Medium
Memory	Size	3000MB	Medium Low
	Type	DDR	Very Low
Hard Disk	Size	500 GB	Medium High
	Type	SATA300	Medium High
Display	Revolution/Sec	5400 Rev/Sec	Medium
	Technology	TFT AM	Very High
Network	Resolution	1024 X 768	Very High
	Modem	56Kb/S	Very Low
Screen Size	Network Connection	802.11b/g 10/100Mb	Very High
	Width	14.00"	Medium High
Sound	Realtek	1.00	Medium
Price	Cost	89,850.00	Medium Low
Power	Battery Durability	4 Hours	Low

In our experiment, the Component Capability Value (CCV) based on laptops' attributes is computed as shown in equation (9) below. For each laptop, a CCV is obtained for all its components and all the CCV are later summed. A value that represents the needs of a consumer is also computed and compared with a vector of summed CCV of all the laptop products retrieved from

the database to find the appropriate products that meet the request. For example, according to the information provided in TABLES II and III. The capability value of the CPU in "DELL Inspiron 14Z" can be calculated by using equation (5) above. The computation is presented as follows:

$$\begin{aligned}
 CCV_{CPU} &= (3, 4, 5) * 0.50 + (6, 7, 8) * 0.05 + (4, 5, 6) * 0.20 \\
 &\quad + (4, 5, 6) * 0.05 + (3, 4, 5) * 0.20 \\
 CCV_{CPU} &= (1.50, 2.00, 2.50) + (0.30, 0.35, 0.40) \\
 &\quad + (0.80, 1.00, 1.20) + (0.20, 0.25, 0.30) \\
 &\quad + (0.60, 0.80, 1.00) \\
 CCV_{CPU} &= (3.40, 4.40, 5.40) \quad (9)
 \end{aligned}$$

The same procedure is followed to compute the CCV for other components. Subsequently, the CCV for all laptop products are obtained. Finally, the capability values of the components *Network, Memory, CPU, Graphics, Hard disk, Screen and Display* in addition to *Battery-life/Price* are used to compute the synthetic capability value of a laptop that will meet the needs supplied by a consumer.

B. Results

Fig.5 shows the typical recommendation results corresponding to the consumer's needs as indicated in Fig. 4. In this result, five laptops out of the 50 laptops in the database were recommended to the consumer, according to the fuzzy near compactness value between the consumer qualitative need and the product synthetic capability. Each recommendation made by the system was rated by signifying its efficiency level with respect to the consumer's needs using the five (5) stars provided after each recommendation, as shown in Fig. 5.

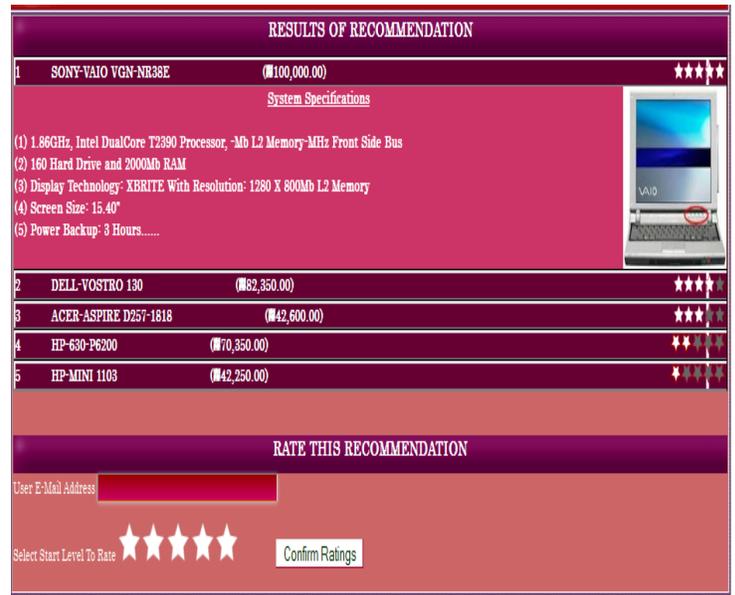


Figure 5: Typical Recommendation Results

TABLE III. TECHNICAL ATTRIBUTES SELECTED FOR LAPTOP COMPONENTS

Component	Technical Attribute(s)	Weight	Sample Specifications
CPU	Frequency	0.5	1.2 GHz, 2.0 GHz, 2.7 GHz
	Manufacturer	0.05	Intel, AMD
	FSB	0.20	400 MHz, 600 MHz, 860 MHz
	Type	0.05	core i5, DualCore, Atom
	L2 Cache Size	0.20	1000 KB, 2000 KB, 4000 KB
Memory	Size	0.75	1GB, 2GB, 6GB
	Type	0.25	DDR, SDRAM, DDR2, DRAM
Hard Disk	Size	0.15	120GB, 320GB, 500GB
	Type	0.55	ATA, SATA
	Rev/Sec	0.30	3200, 5400, 7200
Display	Technology	0.20	TFT AM, Mobility Radeom
	Resolution	0.80	800 x 600, 1280 x 800
Network	Modem	0.30	56Kb/Sec, 1286Kb/Sec
	Network Connection	0.70	802.11b/g 10/100Mb/Sec Ethernet LAN Mini PCI WIFI
Screen Size	Width	1.00`	10.0`, 15.4`, 17.7`
Sound	Realtek	1.00	Medium
Weight	Weight	1.00	400, 360, 530
Price	Cost	1.00	89500, 60000
Power	Battery Life	1.00	4hr, 6hr, 12hr

TABLE IV. RELATIONSHIP BETWEEN CONSUMER NEEDS AND LAPTOP COMPONENTS

Consumer Requirement	Weight	Component
Downloading	0.50	CPU
	0.30	Network
	0.15	Memory
	0.05	Hard Drive
Music	1	Sound
Games	0.25	CPU
	0.2	Memory
	0.25	Graphics
	0.1	Sound
	0.15	Display
Movies	0.05	Hard Drive
	0.4	Graphics
	0.2	Sound
	0.2	Screen
	0.1	Memory
Application Programming	0.05	CPU
	0.35	Memory
	0.10	Hard drive
	0.20	Display
	0.9	CPU
Word Processing	0.1	Memory
	0.65	CPU
Data Analysis	0.35	Memory
	0.2	CPU
Graphics Handling	0.2	Memory
	0.3	Graphics
	0.1	Hard drive
	0.05	Screen
	0.15	Display
Price	1	Price
Weight	1	Weight
Power Consideration	1	Battery Backup
Screen Size	1	Screen

C. Evaluation

In attempt to evaluate the efficiency of the proposed system, 20 experts in the domain of Computer Engineering and Science were randomly selected to use and rate the system. The data obtained from their respective ratings are presented in TABLE V. According to TABLE V, 1.0 means five stars, 0.8 means 4 stars, 0.6 means 3 stars and so on. The average performance of the system based on the data collected from experts' ratings is shown in the table.

TABLE V. EXPERT EVALUATION AND RATINGS

S/No.	Expert ID	Rating
1	E01	1.0
2	E02	0.8
3	E03	0.8
4	E04	1.0
5	E05	0.6
6	E06	1.0
7	E07	1.0
8	E08	1.0
9	E09	0.8
10	E10	1.0
11	E11	1.0
12	E12	1.0
13	E13	1.0
14	E14	1.0
15	E15	1.0
16	E16	0.8
17	E17	1.0
18	E18	1.0
19	E19	0.8
20	E20	1.0

Based on the ratings of experts' presented in TABLE V, we estimated the average performance of the system and its efficiency as given in equations (8 and 9) below.

$$\text{Average } (\bar{x}) = \frac{\sum_{i=1}^n x}{n} \dots \dots \dots (8)$$

$$\text{Efficiency } (Eff) = \bar{x} * 100 \dots \dots (9)$$

After applying equations (8 and 9) to the data in TABLE V, we observed that our proposed recommender system is 93% efficient in recommending optimal laptop products to prospective customers.

V. CONCLUSION

In this paper, we propose a personalized attribute-based recommender system as a solution to less frequently purchased products. Our proposed system incorporates a set of techniques for mining the requirements of customers and the attributes of laptop products, in order to recommend optimal products to prospective buyers of laptop computers. The system is able to provide online buyers with information on the products that could best meet their individual needs. The system also has the potential of increasing sales for online businesses, thereby making online shopping more interesting and profitable to both buyers and sellers.

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AUTHORS PROFILE

Dr. (Mrs.) Bolanle Adefowoke Ojokoh has B.Sc, M.Tech and Ph.D. degrees in Computer Science. She has been involved in teaching Computer Science courses for over 10 years in the Federal University of Technology, Akure, Nigeria. Her research interests include metadata extraction, digital libraries, recommendation systems and gender issues in ICT. She has published several papers in learned journals and academic conferences. She was on Postgraduate and Postdoctoral Research visit to Peking University, China.

Mr. Omisore Mumini Olatunji is a Research Student at the Federal University of Technology, Akure, Nigeria. He Studied Computer Science at Undergraduate Level and currently on his Masters of Technology Degree in Computer Science (Software Engineering and Database System). He has worked for over two years as Research Assistant/System Analyst at High Technology Research and Development Group (HTRDG) Computer Limited, Nigeria. Contact: +2347031967847, ootsorewilly@gmail.com

Mr. Samuel Oluwarotimi Williams has B.Sc. degree in Computer Science and he is currently pursuing a Masters of Technology Degree in Computer Science at the Federal University of Technology, Akure, Nigeria. He has over four years experience in teaching computing courses. He has special interest in computational intelligence, programming, and database administration. He currently works with High Technology Research and Development Group (HTRDG) Computer Limited, Nigeria as a research assistant/system analyst. Finally, he has participated in several ICT projects both in school and at national level. Contact: +2348032397138, timitex92@gmail.com.

Mrs. Temidayo Ogunniyi has B.Tech, degree in Computer Engineering and M.Tech. in Information Network. She is currently working in the department of Computer Science of the Federal University of Technology, Akure, Nigeria. Her areas of research interests include Mobile Networking, Distributed Computing and Mobile Recommended System.