Information Management and Business Review (ISSN 2220-3796)
Vol. 10, No. 3, pp. 17-24, September 2018

A User-Centric Housing Recommender System

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Abstract: Recommender systems are very useful in assisting users to reduce the complexities involved in their decision making processes. It is particularly difficult for people to make decisions on housing choices because different options exist with different facilities, in different locations and with varied cost implications. This paper proposes a hybrid user-centric housing recommender system that is implemented to assist potential house buyers and tenants to generate house listings based on their preferences with the aid of fuzzy logic and item-based collaborative filtering. A virtual tour of the houses is also provided for better choice making.

Keywords: *Recommender System, Fuzzy Logic, Collaborative Filtering, Housing*

1. Introduction

Recommender Systems essentially perform the function of information filtering while dealing with the problem of information overload as they dynamically filter out relevant information from large databases based on user's preferences, interest, or item's observed behavior (Konstan and Riedl, 2012; Pan and Li, 2010). Recommender systems are able to perform the function of predicting the preference of a user about an item based on his profile (Isinkaye et al., 2015). These systems proffer benefits such as reducing the transaction costs of finding and selecting items and revenue enhancements in electronic commerce sites. They have also been proved to improve decision making process and quality (Pathak et al., 2010). Housing is a basic human need and it is a critical determinant for survival. It is seen as one of the most basic human necessities alongside food and clothing (Ikejiaku, 2009). An individual who has an abundance of food and clothing without a house to live in might as well be regarded as an animal (Carpenter et al., 2005). Currently, a person’s choice of housing not only provides the main purpose of protection but goes further to reflect a person’s status in society. As a result of this, people meticulously put a lot of factors into consideration before making a particular choice for a house. According to Aggarwal (2016), the basic recommender approaches are Collaborative filtering, Content-based and Knowledge-based. Collaborative filtering provides a recommendation based on the idea of leveraging the ratings and actions of a user with his community. The content-based approach provides a recommendation based on the attributes that the user has favored in his past ratings and actions, while a knowledge-based approach gives a recommendation based on the user's explicit specification of the kind of attributes he wants.

Knowledge-based recommender systems, essentially leverage user specifications item attributes and domain knowledge. They are particularly useful when dealing with items and services that are not purchased or required very often. These include houses, which is the major concern of this study. An important strength of these systems is the absence of the cold-start problem. The features of these items and the user profile at times are presented in imprecise, uncertain and vague from. Thus, they need to be carefully analyzed for optimal results. Fuzzy Logic is a method that has been found to be very useful for addressing such situation and have been widely applied to handle uncertainty, impreciseness and vagueness in item features and user's behavior in the design of recommender systems (Jain and Gupta, 2018). In some instances, two or more of these basic types of recommender systems are combined to form a hybrid system based on the need at hand. In this research, a hybrid system that utilizes a combination of knowledge-based filtering and item-based collaborative filtering is proposed to recommend houses. It contains a fuzzy logic based component that analyses multiple housing attributes. These attributes typify the profile of the users. It also uses an item based collaborative filtering component for location comparison based on user’s ratings and produces a suggested list expected to depict the preferences of the users, using a case study of Akure metropolis of On do State, Nigeria. Section two of this paper presents the literature review. Section three describes the proposed method. The results of the implemented system are presented in Section four, while Section five concludes the paper.

2. Literature Review

Recommender systems have intuitively come into play to help present the user with exactly what he had in mind to find by taking input parameters from the user that is used in some way to determine what he needs. Recommender systems have been studied and used to suggest items such as books, music, movies, news, and partner matching in dating sites, among others that are of matched interest to a particular user (Schafer et al., 1999; Pizzato et al., 2010; Burke, 2002). Recommender systems give suggestions and recommendations when users need to make decisions while faced with different choices (Ojokoh et al., 2012). Access to information is readily increasing and likewise the information available, so typically on the hunt for information on a particular item, a bulk of information has to be perused to get to that item which the user particularly needs, and in scenarios where the users don't know exactly what they are looking for, this scenario is now even more complicated and most of the time the user only usually finds that particular item by mistake. In order to find associations among items and users, a Recommender System (RS) analyzes data about items or about interactions between users and items (Omisore et al., 2013). It usually provides advice about items to be purchased or examined by users. The results presented as recommendations usually help the users to navigate through large information space of product descriptions, movies, news articles or other items (Burke, 2001). These recommendations can be based on the top overall sellers on a site, the demographics of the consumer, or an analysis of the past buying behavior of the consumer to predict possible future behavior (Omisore & Samuel, 2014).

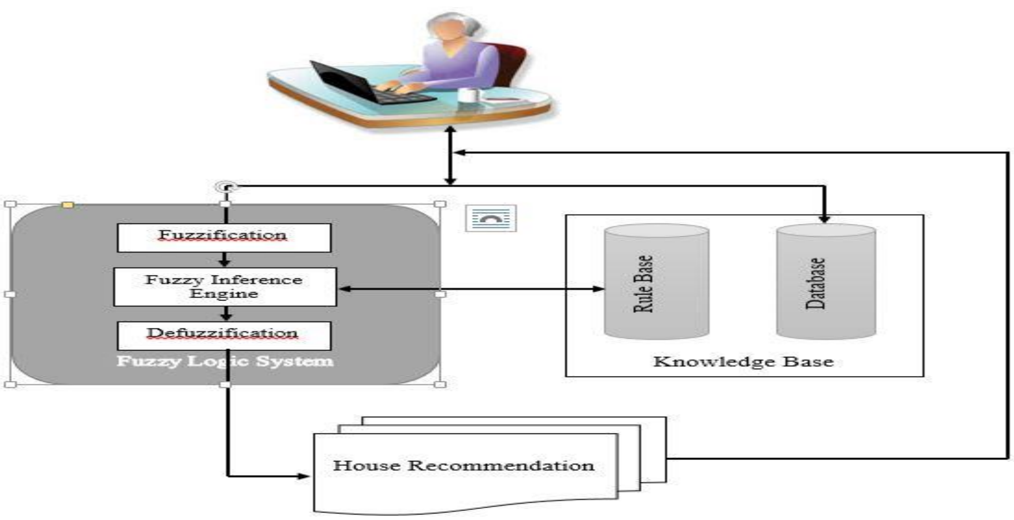
Collaborative Filtering (CF) evaluates items using the opinions of other people (Schafer et al., 2002). A CF algorithm suggests new items or predicts the utility of a certain item for a particular user based on the user's previous likes and the opinions of other like-minded users. For a typical CF situation, there is a list of l users U = $\{u_1, u_2, \ldots, u_l\}$ and a list of n items I = $\{i_1, i_2, \ldots, i_n\}$. Each user u_i has a list of items Iu_i, which the user has expressed his opinions on. Opinions can be given by the user as a rating score, usually within a certain numerical scale, or can be derived from purchase records, by analyzing timing logs or by mining web hyperlinks among other options (Konstan et al., 1997; Terveen et al., 1997). Sarwar et al. (2001) identified User-based CF which could be memory or model-based (Isinkaye et al., 2015) and Item-based collaborative filtering algorithms. One important step in the item-based collaborative filtering algorithm is the computation of the similarity between items and the selection of the most similar items. The basic idea in similarity computation between two items i and j is the isolation of the users who have rated both of the items and then the application of a similarity computation technique to determine the similarity $s_{i,j}$. Such similarity between items could be computed using cosine-based similarity, correlation-based similarity or adjusted-cosine similarity (Sarwar, 2001). Content-based recommendation does not use other people's opinion to recommend but rather recommend items based on a description of an item and the profile of the user.

Content-based methods recommend items that are similar to the ones that the user liked in the past (Lops et al., 2011). It is an information filtering approach where features of items a user likes are exploited for recommendations. Content-based recommender system is dynamic in every way as it learns from the user through the categories of items the user examines and also items the user has previously rated, purchased or viewed (Lops et al., 2011). In general, various candidate items are compared with items rated by the user and the best matching items are recommended. Event though, a content-based recommender makes its comparison with items the users have viewed previously, it solely remains with that particular user. The third type of recommender system is one that uses knowledge about users and products to pursue a knowledge-based approach to generating a recommendation, reasoning about what products meet the user's requirements. Knowledge-based recommender systems are particularly useful in the context of items that are not purchased very often. Such cases include the recommendation of items such as real estate, automobiles, tourism requests, financial services, or expensive luxury goods. Usually, sufficient ratings may not be available for the recommendation process because of the fact that these items are not commonly purchased. In addition, they require different types of detailed options. For items in a Knowledge-based recommender, the nature of consumer preferences may evolve over time as can be found in the example of a car model that may evolve significantly over a few years as a result the preferences may show a corresponding evolution. In other situations, to fully capture user interest with historical data such as ratings might be somewhat difficult. Essentially, in the Find Me system the collaborative filter is only used after the knowledge-based system has done its work (Yuan et al., 2013).

Moreover, it may be that a particular item has some attributes associated with it that correspond to its various properties, and a user may be interested only in some items with specific properties. An instance is in cars that may have several models, color engine and interior options, and user interests that may be regulated by a very specific combination of these options. Thus, in these cases, the item domain tends to be complex in terms of its varied properties, and it is difficult to associate sufficient ratings with the existing large number of combinations (Aggarwal, 2016). Knowledge-based recommender systems could be: Constraint-based recommender systems, where users typically specify requirements or constraints (for example, lower or upper limits) on the item attributes or Case-based recommender systems, where specific cases are specified by the user as targets or anchor points (Lorenzi et al., 2014). A number of works exist in any of the above-outlined approaches or a combination of one with another. For instance, Shanmuganathan and Karthikeyan (2016) proposed a recommendation system for flats availability within Chennai city limits and its surroundings. The system employed the Analytical Hierarchy Process (AHP) for supporting product comparisons and evaluation of consumers. Burke (2002) particularly tries to propose a system that excels above the drawbacks of both the knowledge-based and collaborative recommender system. He proposed a hybrid recommender system (Find Me) for choosing restaurants based on various parameters. The system particularly collects information from its users. It also develops a platform whereby similar ratings are derived from other users' actions in the system, then similarities are looked for from across other users, then these similarities are used to modify the options made available to the user during the tweaking process from the browsing behavior of other users. In Daly et al. (2014), a multi-criteria system for recommending available houses for purchase or rent based on the location of the house, and other locations the user journeys to frequently while factoring the price the house goes for. The system computes travel time between the choice area and the frequently commuted locations, traffic congestions along the routes and recommends a house that gives the minimum travel time at best to locations that are important to the user and suits the user's price range.

3. Methodology

Figure 1: Architecture of the Housing Recommender System



The architecture in figure 1 describes the housing recommender system. It consists of user interface, a medium through which users make interaction with the system, also a medium through which input is given to the system and output is displayed back to the user. The knowledge base includes the database and rule base. The database is a repository for storing information about houses, locations, user preferences, and user comments, user account information, the users account information, house information, entire location information. It serves as a store of information used to process operational data needed by the system. The fuzzy logic engine consists of fuzzification the rule base, inference engine and the defuzzification components which are described below:

Fuzzification: Here, the input variables are fuzzified. Also their respective membership functions are defined. These functions are applied to determine the degree of each input variable. Equation 1 describes the universe of discourse and its fuzzy set.

$$u = \{(x_i \mu_u(x_i)) | x_i \in U, \mu_U(x_i) \epsilon [0,1]\} \qquad (1)$$

where U is the universe of discourse that contains all elements that will be put into consideration, μ_u is the degree of membership of x_i and $\mu_u(x_i)$ represents the membership function (MF) of x_i in U, which is also a real number whose interval is from 0 to 1, and can be derived from equation 2

$$\mu_u(x_i) = \begin{cases} 1 \\ \frac{x_i - a}{b-a} \\ \frac{c - x_i}{c-b} \end{cases} \qquad (2)$$

where a, b, c, are parameters of the membership function from equation (2). After proper consultations with estate agents, attributes needed for the recommendation of houses were obtained. These include house price (very low, low, quite average, fairly high, high), house type (bungalow, duplex, pent house, self-contained, room and parlor self-contained, terraced house, 2-bedrooms flat, 3-bedrooms flat, 4-bedrooms flat, tenement house), house location (rural, low cost area, estate, Government Reserved Area, urban, socialized area). Table 1 shows the House price linguistic variables used to determine price range of houses for users.

Table 1: House Price Linguistic Variables and Fuzzy Value Range

S/N	LINGUISTIC VARIABLE	FUZZY VALUE RANGE	TRIANGULAR FUZZY NUMBER (TFN)
1	Very Low	0 ≤x ≤50000	(0,1,2)
2	Low	50001 ≤x ≤100000	(1,2,3)
3	Average	100001 ≤x ≤1800000	(2,3,4)
4	Fairly High	180001 ≤x ≤350000	(3,4,5)
5	High	x ≥ 350000	(4,5,6)

The Rule Base: The rule base is the second component of the Fuzzy logic system. It is characterized by a set of "IF- THEN" rules, in which the antecedents (the IF part of the rule) and its consequences (the THEN part of the rule) involves linguistic variables.

Inference Engine: The inference engine receives input from rule base and fuzzification interface. It is a decision-making engine that applies suitable procedures formed from the rules in the rule base in order to draw deductions as output. For each rule, the inference mechanism checks the membership values in the condition of the rule. The inference engine technique employed in this paper is the Root Sum Square (RSS). RSS is given by the formula in equation (3):

$$\text{RSS} = \sqrt{(R_1^2 + R_2^2 + R_3^2 + \ldots + R_n^2)} \qquad (3)$$

where R = value of firing rule, $R_1^2 + R_2^2 + R_3^2 + \ldots + R_N^2$ are strength values (truth values) of different rules that also have the same conclusion.

Defuzzification Process: The defuzzification process accepts fuzzy set from the inference engine and converts them to a single crisp value. There are several methods for defuzzification, the Centre of Gravity (COG) was employed for this work. The COG is formula given below:

$$CoG(Y') = \sum \frac{\mu_Y(X_i)X_i}{\mu_Y(X_i)} \quad (4)$$

where (X_i) denotes the center of the membership function and $\mu_Y(X_i)$ is the membership value in the membership function.

Item-Based Collaborative Filtering: The item based approach looks into the set of items the system possesses and computes their similarities to the target item j, the user has selected or rated, it then returns l $\{l_1, l_2, \ldots\ l_n\}$ which are the most similar items to j. Correlation-based Similarity (Sarwar, 2001) is proposed, where similarity between two items j and k is measured by computing the *Pearson-r* correlation. If the set of users who both rated, j and $k$are denoted by U, then the correlation similarity is given by:

$$Sim(j,k) = \frac{\sum_u \in U(R_{uj}-\bar{R}_j)(R_{uk}-\bar{R}_k)}{\sqrt{\sum_u \in U(R_{uj}-\bar{R}_j)^2}\sqrt{\sum_u \in U(R_{uk}-\bar{R}_k)^2}} \quad (5)$$

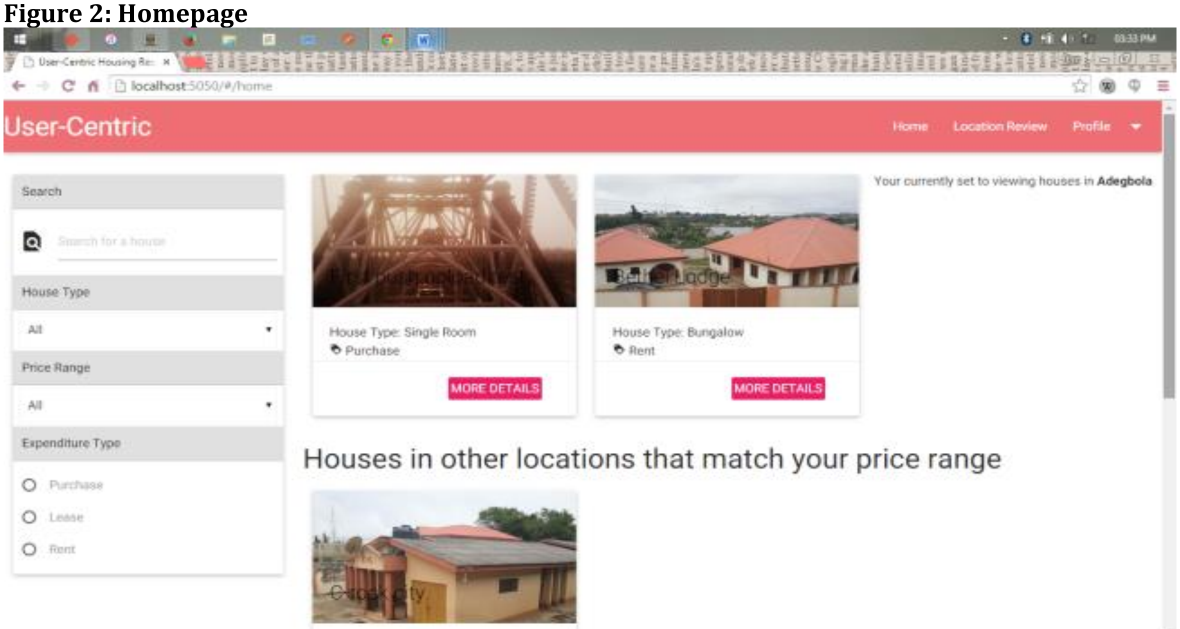
where U is the set of users who rated j and k,
$R_{uj,}$ is the rating of user u on item j,
$\bar{R}$is the average rating of the jth item.

4. Results and Discussion

Implementation: All program codes were implemented using HTML, Node.js and Web GL. HTML tags were employed to structure the way the web pages are displayed; Node JS is a runtime system for creating (mostly) server-side applications. Mongo DB which is a document-oriented DBMS is used as the persistent data store for the application, while Web GL is used through the implementation of three JS to provide a virtual 360-degree showcase of selected houses. This research was implemented as a web application so as to make it easily accessible by users using different varieties of devices. The data sets used were obtained from recognized government approved real-estate agents in on do State, one of the prominent states of Nigeria to create an authentic case study for evaluating the effectiveness of the system.

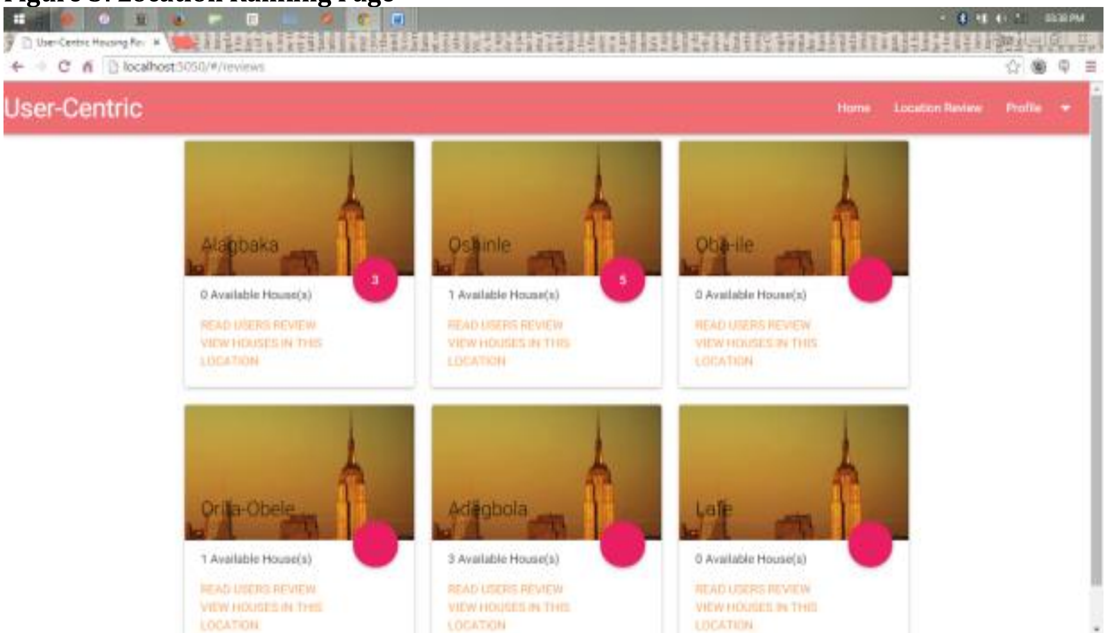
Homepage: The homepage is displayed after a successful login by the user. The home page is where the user gets his recommendations, based on the location he had previously entered in on sign-up. The user also has the option to filter through the recommendation given to him by searching, the house type, and expenditure type.

Figure 2: Homepage



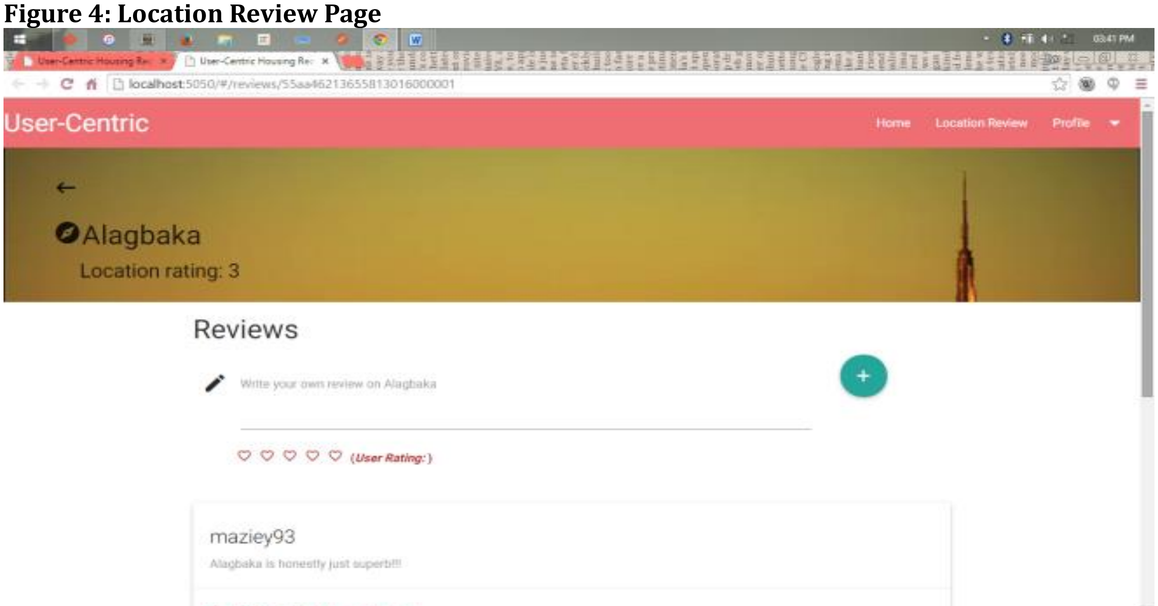
Location Ranking: This page gives the user insight about the location rankings based on the ratings that other users of the system have assigned each location, also from this page user can navigate to read reviews by different users about the location or view the houses in the location.

Figure 3: Location Ranking Page



Location Review Page: On this selected page, users are able to gain insight to a particular location by reading reviews and ratings that other users have given this location and logged in user can also add their own reviews and ratings for the selected location.

Figure 4: Location Review Page



Evaluation: For the evaluation of the developed system, the metrics defined by Lops et al. (2011) for reviewing the efficiency of recommender systems were adopted to actually help determine if the developed system provided any help to the users. The metrics that were chosen as the basis for the system's performance evaluation are: User preferences, User Interface and Experience, Novelty. A simple survey was carried out to evaluate the effectiveness of the user-centric recommender system, using a sample of twenty users. These users included students, housing agents and prospective house renters. The following scales were used to rate the interface and novelty of the system: Very Good (4), Good (3), Fair (2), Poor (1).

Table 2: Results Showing User Interface, Novelty and Experience Ratings by Users

S/N	QUESTION	V.GOOD [4]	GOOD [3]	FAIR [2]	POOR [1]	RATING
1	How easy is it to understand the proposed system?	10	4	5	1	3.15
2	How friendly is the interface design?	12	4	4	0	3.3
3	Did other user ratings affect your choices?	8	3	5	2	2.7
4	How was your experience using the system?	7	10	3	0	3.15
5	How would you rate the virtual tour of the houses?	15	5	0	0	3.75

Each individual question score was calculated by multiplying the score point of the user rating by the user frequency for the particular score point and then further finding the average, so we have the formula;

$$\frac{\sum_{i=1}^{4} f x_i}{4} \qquad (6)$$

To calculate the total average rating for the system;

Average system rating = $\frac{3.15+3.3+2.7+3.15+3.75}{5}$

= 3.21

5. Discussion and Conclusion

The results also show that 50% of the sample population found the proposed system relatively easy to understand and rated the ease of use of the system a score point of 4, while another 20% and 25% rated the system score points of 3 and 2 respectively. This might be due to the fact that systems that proffer similar solutions already exist. Only 5% of the respondents rated the ease of use of the system poor. 60% of the sample population found the system very friendly to use and rated the system a score point of 4, while 40% rated user-friendliness a score point of 2 and 3. No percentage of the respondents rated the system poor for user-friendliness. 44% of the sample population found that the choices of users in the system were affected by ratings of other users in the system. Another 28% of the user establishes the idea that the rating of other users is a factor which influences the choice new users make. 35% of the sample population found the user experience of the system to be very good, while 50% of the population found the user experience to be good, in total a very large proportion of the sample population all found the user experience of the system to be good.

The virtual tour implementation of the houses was designed to give the users a way for them to see the house completely in 3D; the virtual tour experience was rated 75% by the sample population and they found the virtual tour experience to be very good. The remainder 25% of the sample population also found the tour to be good. This generally shows that the ratings of the respondents with regards to virtual tour experience provided by the system is very good as well as provide good pictorial and qualitative information about the property. In fact, it is inferred from the data presented that the virtual tour was what most respondents liked the most about the system.

Conclusion: Housing remains a basic need of mankind which cannot be overemphasized. This paper addresses the design and implementation of a housing recommender system that matches a user's preferences with houses that suite his needs. The research explored fuzzy logic for analyzing the multiple housing attributes and Pearson correlation coefficient to aggregate the rating of users on locations. A virtual tour of the houses is also provided for better choice making. An evaluation of the system was conducted with twenty users' experience. In the future, the methods presented in this work, can be elaborated further with more datasets and a broader level of experiments can be carried out.

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