B2C Mapping Based On A Fuzzy Logic Recommender System

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***Abstract*—Saving time and effort in searching for products and services is becoming an important issue in people's daily lives with the existence of new supporting technologies. Advanced search engines, directed advertising, and recommendation systems are all examples of such technologies. The services provided by restaurants are improved lately due to the utilization of different technologies in providing their services. Customers (or clients) require searching for the optimal services provided by the restaurants with minimal time, cost, and effort. This work is related to enhance the process of searching for the best restaurants' meals by implementing a tool supported by a fuzzy-based recommendation system that maps the best restaurants to customers' needs. The tool enables the customers to search for restaurants that satisfy their desires either manually or by relying on the fuzzy-based technique. The searching technique developed in the work helps customers to search and to get a list of the best-ranked restaurants related to their searching criteria. The experimental tests conducted in the work emerge a promising reduction in time and cost compared to the ordinary searching of meals.**

***Index Terms*—Recommendation System, Fuzzy Logic, Ranking Technique, Cost Reduction, Time Reduction.**

I. Introduction

The mapping between service seekers and service providers is becoming a need these days. From the customers' point of view, the reduction of consumed times and paid efforts in finding the best service providers within a reasonable amount of cost is an important issue [12]. Moreover, customers need to find the best service providers that match both their needs and their ability to afford services. On the other side, and from providers' point of view, providing services does not rely on just showing the services to customers and waiting for their desire to buy, it goes beyond that by developing techniques in reaching customers. These directions of demands created a necessity to find proper ways to make the best mapping between service providers and customers [2].

Directed advertising, service mappings, and inventing recommendation systems are all examples of different modern techniques to map between customers and service providers. However, relying on the customers' experiences in searching for the proper services does not provide the best way for finding the optimal provided services. Due to this, service providers rely on other techniques to make it easy for customers to search for their desired services that fit their needs. One of these techniques is to enhance the searching for services by introducing a proper recommendation system that better maps the customers with the services' providers [3]. Personalizing and recommending resources to customers save time and effort and hence costs of finding the proper services. Recommendation systems have been widely used in applications as they have become an important field of research, helping users deal with big data and making it easier to search for what they need.

One of these services is the ones related to restaurants because they have a direct impact on the service offering and they are directly related to economics, especially when it is related to tourism. With a large number of restaurants and the tremendous amounts of provided meals, it becomes hard for customers (and also tourists) to search and find the proper meal that sometimes matches their culture and desires (especially in the case of tourists). Because of this, it becomes mandatory for the customers to be mapped with the best restaurants that match their requests [9].

One of the techniques to make it easier for the customers to search for service providers, and in our case: the restaurants, is to enhance the searching for restaurants with the support of a suitable recommendation system that takes into account the needs of the customers and the abilities of restaurants to provide the customers with the best rank of meals [1]. With the large number of restaurants spread around cities and towns, it has become necessary to distinguish which restaurants provide the best services to customers. The task of manual searching for a restaurant that offers high-quality food at a reasonable price and satisfying services is not an easy task.

Recommendation systems can be implemented in several ways. Collaborative, Content-based, Demographic-based, Utility-based, and Knowledge-based are all examples of different techniques used to implement the recommendation systems [6]. However, with the case of a restaurant search, customers usually have different criteria (could contradict some times) with respect to the type of services they need within a limited amount of cost that makes the process of finding the best restaurants to fulfil their needs is hard. However, Fuzzy logic-based recommendation systems are the most suitable recommendation in such cases due to their nature in dealing with the fuzziness needs of customers [4].

In this work, we are developing a mobile-based tool [1] to

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[1]The terms: *tool*, *system*, and *application* are all related to the implementation of this work.

make it easy for customers to search for restaurants according to their needs and abilities. The tool enables the customers to manually search for restaurants as well as giving them the ability to use the embedded fuzzy logic-based recommendation system to help them find the best restaurants that offer the wanted meals. The tool has a set of functionalities to make it easy for customers as well as restaurants to communicate and collaborate to accomplish needed tasks upon the requests directed from customers to restaurants. The related data are stored in a special database to be used by the recommendation system. The conducted experimental test emerged a minimal time, effort and cost to accomplish tasks compared with the manual arrangement between customers and restaurants.

The rest of this paper is organized as follows: Previous work is proposed in Section II. Section III discusses the system architecture of the implemented work while section IV is related to the implemented fuzzy-based recommendation system. Section V discusses the experimental test and finally, Section VI concludes this paper.

II. Related Work

The involvement of different recommendation systems techniques in most of the applications is used to tailor the needs of customers according to the services they desire. It is some kind of optimization technique used to get the most of the provided services in users daily lives. It provides smarter and faster shopping where users need the optimal services with minimal amounts of time, effort and cost [5].

Recommendation systems are of great use and importance due to their direct impact on facilitating user's tasks [11]. Service providers rely on recommendation systems in directing their services to a majority of customers according to their needs. There are several types of recommendation systems like Collaborative, Content-Based, Demographic Based, Utility-Based, Knowledge-Based and Hybrid.

Fuzzy logic-based recommendation systems are famous and a lot of published works adopt them in the design and implementation of their recommendation systems [10]. Authors of the work presented in [8] propose a personalized recommendation system driven by fuzzy logic technique for products that target recommending optimal products to prospective buyers, promoting the rate at which customers visit online stores and eventually increases sales for online businesses.

Due to the COVID-19 pandemic, the rely on online services were increased [7]. With respect to services offers by restaurants, there are many universal applications that make it easy for the user to order meals remotely. *DoorDash* [2] application works on both IOS and Android platforms. It offers a variety of services and enables customers to easily communicate with the involved restaurants. *GrubHub* [3] offers free delivery services with more than 5000 involved restaurants. It has a friendly interface that makes it easy for users to handle meals delivery easily.

In Palestine, several delivery applications are used. Each of which has its own facilities and properties. Examples include: *Yummy* [4], *Food On Time* [5], *Catch Food* [6], *Wajabaati* [7], *Order* [8], and *Cooknet* [9]. Despite the excellent facilities these tools have, they lack the facility of recommendation system that better maps restaurants to customers according to their requests.

However, part of the tools and applications mentioned above support customers with enough information regards the involved restaurants but most of them lack the ability to involve proper recommendation systems (at least to the time of writing this paper). However, this work takes into account the fulfillment of customers' requests with respect to their needs and abilities by implementing a fuzzy-based recommendation system taking into account the overall satisfaction of customers and the distances between customers and restaurants locations.

Our contribution in this work can be summarized as follows:

1) The ability to evaluate the restaurants by customers according to different criteria (this will be used as a fuzzy variable, the meal cost is the second).
2) The involvement of the meal-wise fuzzy-based recommendation system in order to suggest customers with the best meals provided by some restaurants.
3) The ability to find the minimum delivery distance between the delivery persons and the customers' locations.

III. System Architecture

In this section, we provide an illustrative overview of the tool and its structure, showing its main components and their functions. Before that, we will illustrate the types of users who will be in direct contact with the tool. Those users are of four categories: *customers*, *restaurant owners*, *delivery staff*, and *tool administrator*. All activities carried out by the four categories of users are done via an Android application that includes necessary database transactions to manage their own data in the database. Here are the illustrations for each category:

- **The administrator**: can control all database transactions related to the other users in order to manage the tool services. Restaurants addition, requests for deletion are examples of his/her duties.
- **The restaurant owner**: control the meals on the digital menu, adding and removing delivery staff to and from the tool, s/he can receive customers' orders and then transfer them to the delivery employee if the required meals are prepared.
- **The customer**: customers here can order the meals they want in two ways: (1) by choosing a specific restaurant from the list of restaurants included in the application and then entering the restaurant page and choosing the meals they want from within the list of meals provided by the restaurant, and (2) by displaying all meals appear in the tool and choosing a specific meal and asking the tool to suggest the best restaurants that offer this meal based on the price or the quality of service or both, with the ability to order more than one meal and put them at the order cart

[2]http://doordash.com
[3]http://grubhub.com
[4]https://yummy.ps/
[5]https://foodontime.com.ps/
[6]https://www.catchfood.com/
[7]https://www.wajabaati.com/
[8]https://the.ordering.app/
[9]https://cooknet.me/

and then request them with the ability to determine the locations of delivery if they are different from the already saved ones in customers' profiles. Of course, customers are able to support their accounts with the necessary data to be used by the fuzzy logic-based recommendation system that will be described later on. Moreover, they are allowed to fill confidence applications about the services they got. The data filled in these applications are used to compute the restaurants' ranks. These calculations will be illustrated later on when we describe the fuzzy logic recommendation system.

- **The delivery staff**: users of this account receive the requests from the restaurant owner account, along with the location of the customers to whom the orders are to be delivered. The tool draws a map for each delivery showing the shortest path to follow the delivery location.

A. System Components

The tool is composed of a set of integrated components, each of which is responsible to provide some services.

1) **Database**: We used *Firebase* as a DBMS in this work. All system transactions are saved in a dedicated database. Figure 1 below depicts the system Entity-Relationship diagram showing the main entities (attributes are omitted for paper size limitations). The *user* entity includes all the data describing the users of the system that previously mentioned. The entities *client*, *restaurant*, *delivery*, and *admin* all inherit from the *user* entity. Each of which contains its own data and the ones inherited from the *user* entity. The *restaurant* entity is not more than the owner of the restaurant or some one from its administrative staff, and the same for the *delivery* entity. The *order* entity is to save the orders related data. The *meal* entity is used to save the data related to all meals per restaurant that is connected with the *appetizer* entity.

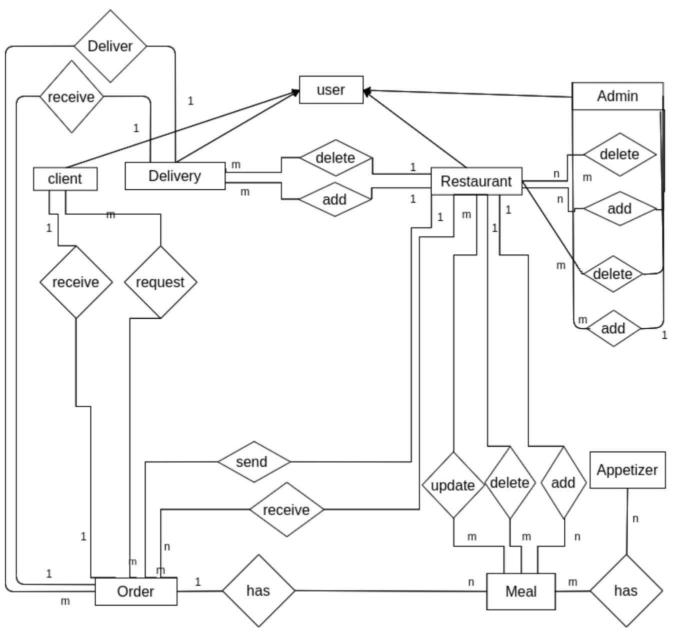

Fig. 1: System Entity Relationship diagram with details about entities and relations.

2) **GPS service**: When a meal request reaches the delivery employee, the application creates a map (on the device of the delivery employee) showing the location of the customer with the shortest path between the customer and the location of the delivery person where *MapBox* [10] API is used for this purpose.
3) **Recommendation System**: Although the system provides full database transactional activities, this part of the system represents the main part of the work and will be illustrated deeply in the following section.

IV. Fuzzy-Based Recommendation System

As mentioned earlier, customers can either directly select the restaurants they prefer or they can manually search for restaurants names and then in both cases accomplish their orders. However, sometimes customers need the optimal restaurants offering the meals they request, or they are strange in a town and they need the best restaurants. In this case, they can ask the application to suggest the most suitable restaurants according to some criteria. The application as a result executes the needed calculations embedded in the fuzzy-based recommendation system to generate a ranked list of the related restaurants. Figure 2 depicts the sequence diagram of utilizing the fuzzy-based recommendation system.

Figure 3 depicts the output for using the fuzzy-based recommendation system by listing some related restaurants each of which with its corresponding rating value.

A. Fuzzy Variables

The fuzzy-based recommendation system implemented in this work is based on two Fuzzy Variables: **Quality** and the **Price**. The first variable is derived from the evaluation forms filled by the customers after they got their meals. The form is composed of several criteria attributes that are used to evaluate the meal of the restaurant. Each of these elements is given a weight value in order to emphasise its importance in the formula that calculates the evaluation of the meal. These criteria elements with their weights are: *Deliver Time (DT)*, *Meal Packaging (MP)*, *Meal Quality (MQ)*, *Meal Appearance (MA)*, *Meal Freshness (MF)*, *Meal Cleanliness (MC)* and *Delivery Person Appearance (DA)* with values: 0.2, 0.05, 0.3, 0.05, 0.2, 0.1, and 0.1 respectively. By this, the quality of some meal represented by Q prepared by some restaurant is given by the formula:

$$Q = DT*0.2 + MP*0.05 + MQ*0.3 + MA*0.05 + MF*0.2 + MC*0.1 + DA*0.1 \quad (1)$$

where the values of mentioned criteria elements are the accumulative values of each evaluation form filled.

B. Inference Engine

As we mentioned before, the fuzzy logic inference engine relies on two fuzzy variables: **Quality** and **Price**. Fuzzy intervals for **Quality** are: $0 - 0.40$ (bad), $0.20 - 0.60$ (fair), $0.40 - 0.80$ (good), and $0.60 - 1$ (excellent) while the intervals of **Price** are: $10 - 15$ (cheap), $12.5 - 17.5$ (moderate), $15 - 20$

[10] https://www.mapbox.com/

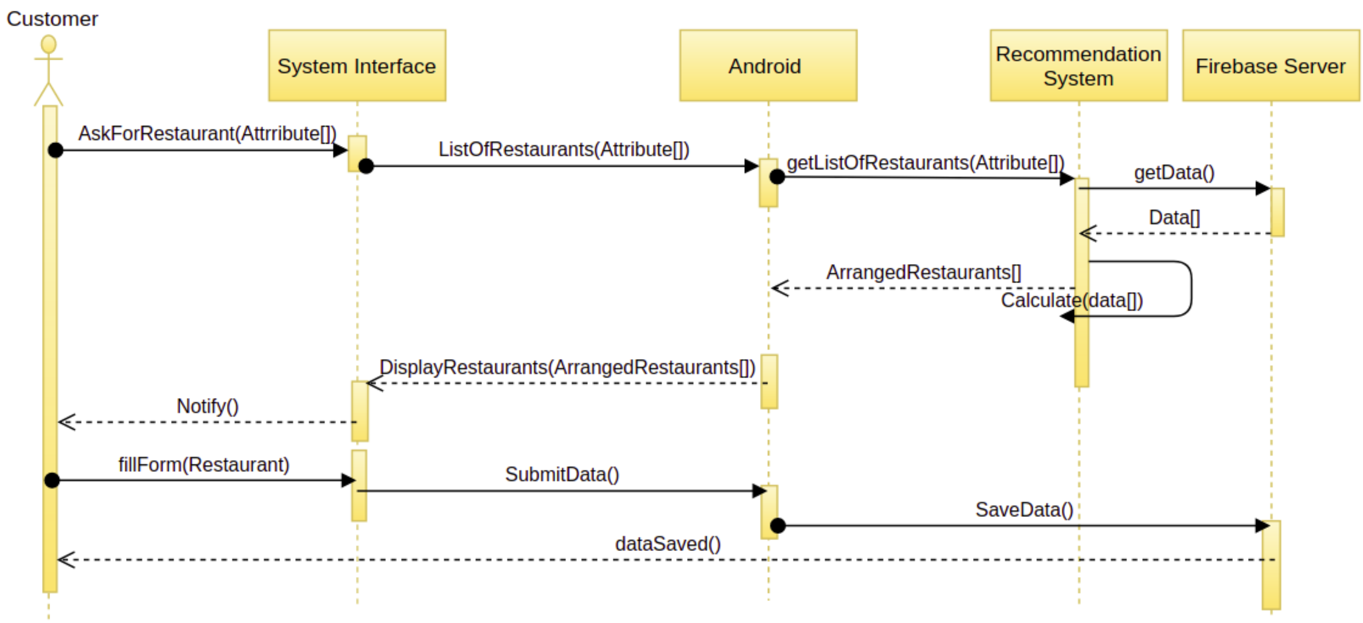

Fig. 2: Sequence diagram for requesting Meals from Restaurants .

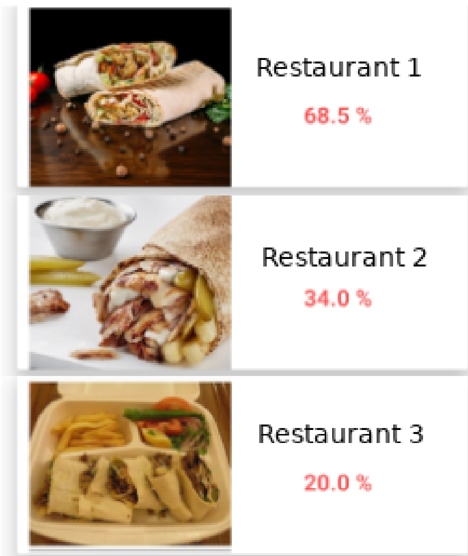

Fig. 3: Raked Recommendation System Suggestions of Restaurants

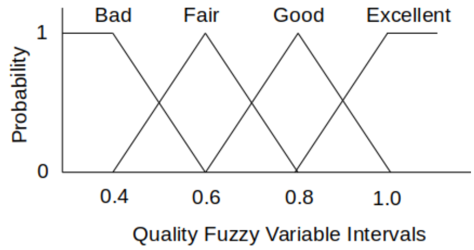

Fig. 4: Intervals of the Fuzzy Variable *Quality*.

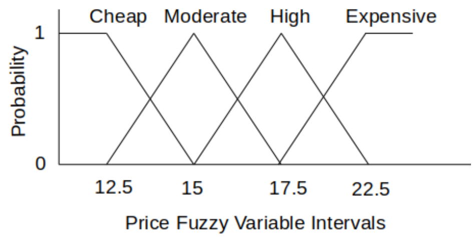

Fig. 5: Intervals of the Fuzzy Variable *Price*.

(high) and $17.5-22.5$ or more (expensive). These intervals are fixed according to some survey conducted for this work. The price values are fixed according to the current money used in Palestine. Figures 4 and 5 depict the graphical representation of both **Quality** and **Price** fuzzy variables.

Table I represents the possible values of combining the two fuzzy variables **Quality** and **Price** where the combination of them provides a different linguistic value. For example: if **Qulaity** is Good and **Price** is Cheap, the output will be **Very Good**. Again, the determination of these values is done according to a survey with a set of restaurants. However, the fuzzification and defuzzification processes depend on this table in order to generate ranks of restaurants to customers by applying the *And* operator on fuzzy sets. Figure 6 depicts the values of the result fuzzy variable. The values from 1 to 7 appear in the *x-axis* of the figure are used as weights in the defuzzification process.

	Bad	**Fair**	**Good**	**Excellent**
Cheap	Moderate	Good	Very Good	Superior
Moderate	Accepted	Moderate	Good	Very Good
High	Bad	Accepted	Moderate	Good
Expensive	Very Bad	Bad	Accepted	Moderate

TABLE I: The combination of the two fuzzy variables: **Quality** and **Price**.

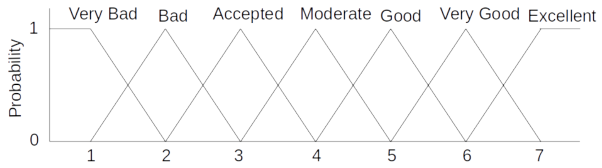

Fig. 6: Intervals of the result Fuzzy Variable.

C. *Defuzzification Process*

To obtain final crisp value for both **Quality** and **Price**, a defuzzification process is executed depending on the **Centre of Gravity for Singletons** formula:

$$CrispValue = \frac{\sum_{i=1}^{n} \mu_i \times o_i}{\sum_{i=1}^{n} \mu_i} \tag{2}$$

where o_i is the corresponding value for the output variable of index i, μ_i is the membership function after accumulation for that variable, and n is the number of variables.

D. *Illustrative Example*

To illustrate how the fuzzy logic recommendation techniques is used in this work, we will go on with an example illustrating the different calculations to generate a ranked list of restaurants based on some suggested numbers for both of the linguistic variables. A client C needs to use the tool to search for Pizza. S/He needs to use the recommendation system for restaurants to provide the meal. Two restaurants $R1$ with quality value 0.55 and price value 18 and $R2$ with values 0.79 and 20 for quality and price, respectively. In this case, the ranking of the two restaurants are calculated as follows:

For $R1$:

- For Quality:
  - $\mu(Bad) = \frac{0.55-0.40}{0.60-0.40} = 0.75$
  - $\mu(Fair) = \frac{0.60-0.55}{0.60-0.40} = 0.5$
- For Price :
  - $\mu(Expensive) = \frac{18-17.5}{22.5-17.5} = 0.1$
  - $\mu(High) = \frac{22.5-18}{22.5-17.5} = 0.9$

Now, from Table 1, we can compute the following:

- if Bad and Expensive then Very Bad, so $0.75 \cap 0.1 = min(0.75, 0.1) = 0.1$
- if Bad and High then Bad, so $0.75 \cap 0.9 = min(0.75, 0.9) = 0.75$
- if Fair and Expensive then Bad, so $0.5 \cap 0.1 = min(0.5, 0.1) = 0.1$
- if Fair and High then Accepted, so $0.5 \cap 0.9 = min(0.5, 0.9) = 0.5$

As a result we have:

- $\mu(VeryBad) = 0.1$
- $\mu(Bad) = max(0.75, 0.1) = 0.75$
- $\mu(Accepted) = 0.5$

Depending on the intervals' values in Figure I, we can compute $R1$ rank: $R1 = \frac{1*0.1+2*0.75+3*0.5}{0.1+0.75+0.5} = 2.29$ represented by the shaded area appears in Figure 7 below.

Similarly, for $R2$:

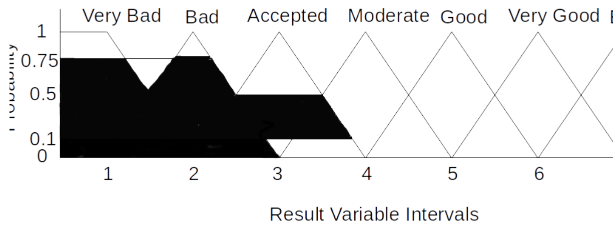

Fig. 7: Intervals of the result Fuzzy Variable for $R1$.

- For Quality:
  - $\mu(Fair) = \frac{0.79-0.60}{0.80-0.60} = 0.95$
  - $\mu(Good) = \frac{0.80-0.79}{0.80-0.60} = 0.05$
- For Price :
  - $\mu(Expensive) = \frac{20-17.5}{22.5-17.5} = 0.5$
  - $\mu(High) = \frac{22.5-20}{22.5-17.5} = 0.5$

Now, from Table 1, we can compute the following:

- if Fair and Expensive then Bad, so $0.95 \cap 0.5 = min(0.95, 0.5) = 0.5$
- if Fair and High then Accepted, so so $0.95 \cap 0.5 = min(0.95, 0.5) = 0.5$
- if Good and Expensive then Accepted, so $0.05 \cap 0.5 = min(0.05, 0.5) = 0.05$
- if Good and High then Moderate, so $0.05 \cap 0.5 = min(0.05, 0.5) = 0.05$

As a result we have:

- $\mu(Bad) = 0.5$
- $\mu(Accepted) = max(0.5, 0.05) = 0.5$
- $\mu(Moderate) = 0.05$

Depending on the intervals' values in Figure I, we can compute $R2$ rank: $R2 = \frac{2*0.5+3*0.5+0.4*0.05}{0.5+0.5+0.05} = 2.4$ represented by the shaded area appears in Figure 8 below.

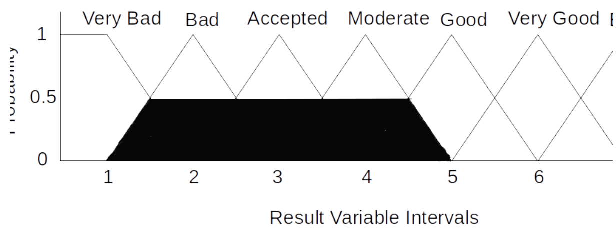

Fig. 8: Intervals of the result Fuzzy Variable for $R2$.

since the value of $R2$ is bigger than the value of $R1$. So, $R2$ comes before $R1$ in the ranking of the two restaurants.

V. EXPERIMENTAL TESTS

In order to examine the recommendation system embedded in our tool, we conducted an experimental test to compare the manual searching for restaurants against the fuzzy-based recommendation system with respect to both time and cost.

We asked 15 volunteers to participate in this test. The sample of volunteers was chosen randomly and they don't know each others. The sample is composed of two subsets: *Customers* and *Restaurants*. In order to test all possible ways of coordination between both sets, we categorized the test into

3 stages, where time and cost were measured in each stage for comparison purposes:

- *Ordinary search for restaurants (without using the tool)*: We supplied the set of customers with the names of some restaurants (even without their phone numbers) and we asked them to begin the process of asking for some meals from the list of restaurants they have. Meanwhile, we computed the time needed and cost spent starting from the initial request of meals till the final delivery of the requested meals. We computed the cost of mobile phone calls spent in the process of dialling restaurants and asking them about the meals they provide.
- *Manual Search (using the system)*: In this stage, we asked the same customers involved in the previous stage to use the tool in order to manual search for restaurants saved in the system. As in the previous stage, we computed the spent time and cost. However, the cost here is related to the connection time of mobile to finish the search for proper restaurants.
- *Using The Recommendation System*: The same customers are asked in this stage to use the embedded recommendation system to allow the tool to suggest the best restaurants regards the required meals. Also, as before we computed both the spent time and cost. The same as stage 2, the cost here is represented by the connection cost needed to finish the stage.

Table II summarizes the collected data during the experiment. The title *Ordinary* with its 2 related columns represent the amount of time and cost spent during the search for restaurants without using the tool. The title *Manual* is related to the time and cost spent with respect to the manual search of the tool. Finally, the *Recommendation* column is related to the time and cost spent using the fuzzy-based recommendation system. A reader could notice the degradation in both time and cost with the usage of the recommendation system which reflected in Figure 9 that depicts the data appear in Table II.

TABLE II: The amounts of spent time and paid cost in the test.

	Ordinary		**Manual**		**Recommendation**	
User	**Search**	**Cost**	**Search**	**Cost**	**Search**	**Cost**
1	20 min	$8	12 min	$0.5	2 min	$0.2
2	18 min	$4	9 min	$0.5	1 min	$0.2
3	15 min	$3	7 min	$0.5	1 min	$0.2
4	10 min	$2	6 min	$0.5	1 min	$0.2
5	25 min	$9	13 min	$0.5	3 min	$0.2
6	30 min	$10	17 min	$0.5	5 min	$0.2
7	23 min	$8	14 min	$0.5	4 min	$0.2
8	42 min	$6	23 min	$0.5	5 min	$0.2
9	19 min	$8	10 min	$0.5	2 min	$0.2
10	20 min	$10	9 min	$0.5	1 min	$0.2
11	35 min	$11	16 min	$0.5	4 min	$0.2
12	21 min	$3	10 min	$0.5	2 min	$0.2
13	16 min	$5	8 min	$0.5	1 min	$0.2
14	44 min	$13	21 min	$0.5	5 min	$0.2
15	27 min	$10	16 min	$0.5	4 min	$0.2

VI. Conclusion

Online purchasing is getting noticed more and more especially with the situation of pandemic diseases that enforces customers to search for the best services with the optimal amounts of time, effort and cost. In this work, we implemented and tested a fuzzy-based recommendation system embedded in a tool used to make an online request of restaurant meals taking into account two fuzzy variables: the *Quality* and the *cost* in which the first variable values are computed depending on the accumulated data gathered by the evaluation forms of customers about the restaurants. The experimental results emerge the degradation of time and cost when using the recommendation system embedded in the tool.

For future works, we plan to provide more features for the system, such as: expanding the system's scope to include services other than providing meals, to include restaurants outside the borders of Palestine, and to include operating systems of handheld devices.

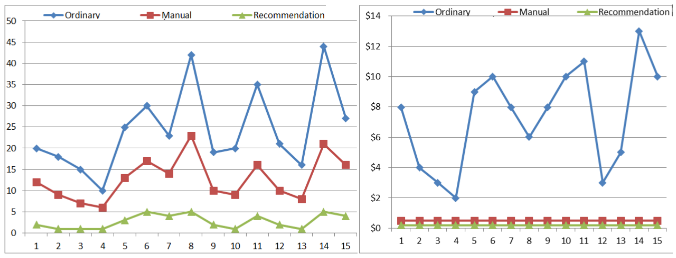

Fig. 9: Comparison between Ordinary, Manual and Recommendation Searching for Artisans in Terms of Time (left) and Cost (right).

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