Content-Based Recommendation System for Craft Owners Based on User Preferences and Availability

Raghad Alia
Department of Computer Science
An-Najah N. University
Nablus, Palestine, P.O.Box:7
www.najah.edu
raghad_alia@hotmail.com

Islam Msalam
Department of Computer Science
An-Najah N. University
Nablus, Palestine, P.O.Box:7
www.najah.edu
islammsalam2002@gmail.com

Amjad Hawash*
Department of Computer Science
An-Najah N. University
Nablus, Palestine, P.O.Box:7
www.najah.edu
amjad@najah.edu

***Abstract*—This study offers a content-based recommendation engine to connect clients with craft service providers based on user-defined preferences, including addresses, preferred timetables, and problem descriptions. The system preprocesses textual descriptions using natural language processing (NLP) techniques and then employs TF-IDF vectors to determine similarity scores. Temporal availability information is also incorporated to increase the accuracy of recommendations. The studies' results demonstrate the value of the system in offering personalized recommendations.**

Index Terms*—Recommender System, Content-Based Filtering, Natural Language Processing, Craft Services, Text Similarity.

I. INTRODUCTION

There are several reasons why it can be difficult to find a trustworthy and knowledgeable tradesman [1]. First of all, it might be challenging to locate and schedule highly trained tradesmen because the demand for fine craftsmanship frequently outweighs the availability. Furthermore, not all professionals will be appropriate for a given assignment due to the variance in skill levels and specializations among craftsmen; this calls for rigorous screening and suggestions. Some trades lack formal certifications or credentials, which can make it more difficult for clients to evaluate skills because they have to rely on word-of-mouth recommendations, reviews, and personal evaluations. Aligning expectations and timelines can sometimes be challenging due to scheduling issues and communication problems. The combination of all these elements makes finding the ideal craftsman a laborious and frequently tedious process.

Employing unskilled artisans can have detrimental effects on the economy [2]. Inadequate craftsmanship frequently produces inferior products that may need expensive repairs or replacements, raising the total cost of the project. This can lead to structural problems that jeopardize safety in sectors like construction, which could result in legal ramifications and increased insurance costs. Long project deadlines can cause delays that interrupt operations and add to costs for both businesses and households. Moreover, using unskilled workers can damage a company's brand and result in lost business and decreased revenue in the future [3]. Since inefficient work results in resource waste and lost output, it is important to invest in skilled workers for long-term economic stability. This could have an impact on the larger economy as well.

To maximize sales and reach the correct audience, craft businesses must overcome several obstacles. The fiercely competitive market, where it might be challenging to differentiate its items from mass-produced commodities, is one of the main problems. Inadequate marketing resources and proficiency frequently impede their capacity to proficiently endorse their crafts, consequently diminishing their visibility among prospective clientele [4]. Finding a focused audience interested in particular sorts of crafts can be difficult as well, given the specialized nature of many handcrafted objects. To reach a wider, more varied client base, craft proprietors also have difficulty utilizing and comprehending Internet marketing tools and platforms. Their attempts to sustain steady sales are made more difficult by the erratic nature of consumer preferences and demand. Craft business owners find it difficult to connect with the right customers and get the best possible sales results when these issues are combined [5].

Systems for making recommendations are essential for improving user experience and producing profitable results for businesses. Through the use of algorithms to evaluate user preferences and behaviors, these systems can provide tailored goods and services that cater to specific preferences and requirements. Customers are given appropriate options without having to search far and wide, which makes for a more rewarding and engaging user experience [6]. Recommendation systems increase the probability of conversions and repeat purchases, which helps organizations increase sales and consumer loyalty. By highlighting products that have a higher chance of their relevance the effective management of inventory by lowering instances of overstock and understock. Recommendation systems can also provide valuable insights

Corresponding Author: amjad@najah.edu

for product development and marketing initiatives, helping companies to better satisfy customer needs and achieve a competitive advantage [7]. All things considered, recommendation systems are an effective means of generating value in today's data-driven economy for both consumers and companies.

Our research intends to create a recommendation system that suggests appropriate artisans based on the user's desired appointment times and a detailed description of their situation to address the prior problems [8]. The system categorizes craftsmen according to their relevance to the current scenario by using 3 relevancy measures: *Cosine*, *Dot Product*, and *Euclidean* similarity measures. In addition, the system considers the availability of craftsmen on the days requested by the customer, guaranteeing prompt and effortless scheduling of appointments [9]. Users can interact with the system by entering their service requirements, which are preprocessed to facilitate comparisons with artisan profiles. Subsequently, the system ascertains which craftsmen best meet the user's needs based on factors such as address, availability, and service relevancy. The ability for users to select a time for their appointment and browse the artisans who have been recommended streamlines the scheduling process considerably.

This study aims to evaluate the effectiveness of our system in terms of enhancing user experience by reducing search time and boosting appointment booking accuracy. Our objective is to demonstrate, via extensive testing and analysis, how our technology genuinely meets user needs and provides reliable recommendations, transforming the way individuals engage with knowledgeable craftspeople in the contemporary digital landscape. The system locates key terms and idioms that match the skills and knowledge listed in artisan profiles by looking through the problem description that the user has provided. Users can be sure that craftsmen with the necessary skills will be connected to them through semantic comprehension. In addition to matching capabilities, the system favors artisans who are available on the days that the user requests. This feature reduces wait times and boosts productivity by allowing users to schedule appointments at times that are most convenient for them. Our system's craftsmen profiles are dynamic and changeable in real time. In addition, the system incorporates a feedback mechanism that allows customers to evaluate and rank their interactions with craftspeople following each service.

The rest of this paper is organized as follows: Previous work is proposed in Section II. Section III discusses the problem statement of the work. Section IV discusses the system architecture of the proposed work. Section V demonstrates the experimental results. Finally, Section VI concludes this paper.

II. RELATED WORK

Numerous domains have seen extensive study and application in the field of content-based recommendation systems [10]. Important works on content-based recommendations are reviewed in this area, with special attention on service providers and scheduling.

Recommendation systems that are content-based examine an item's attributes and suggest related products based on those attributes. The work of [11] has highlighted the use of the term frequency-inverse document frequency (TF-IDF) for content analysis and similarity measurement as one of the foundational studies in this field. These methods have been improved and modified to recommend a wide range of goods, including services and products as well as books and movies.

Healthcare [12] and tourism [13] are two examples of domains where recommendation systems have developed to fulfill particular needs. To provide tailored recommendations, these systems usually take into account contextual data, user preferences, and service qualities. By concentrating on craft owners' recommendations and incorporating user preferences and availability into the recommendation process, our approach expands on these ideas.

Numerous contexts have tackled the problem of scheduling and availability matching, such as healthcare appointment scheduling (Kao, 2008) and personal service booking systems (Wang, 2005). The goal of these systems is to assign time slots as efficiently and satisfactorily as possible. Similar approaches are used by our system to pair users with craft owners according to availability and service relevancy.

Research has focused on how to integrate user preferences into recommendation systems. According to research, user happiness and engagement are higher in systems that adjust to their preferences [14]. To customize recommendations, methods like machine learning, hybrid filtering, and collaborative filtering have been used. Our system uses a content-based methodology to customize recommendations according to the problem descriptions and days that the customer prefers, making sure that the proposed craft owners fit their requirements and timetables.

Recommendation systems have attracted a lot of attention when applied to home and craft services. Algorithms are used by platforms like TaskRabbit and Thumbtack to match service providers with consumers, accounting for variables including availability, proximity, and service ratings [15]. These systems, however, frequently rely more on user evaluations and availability rather than in-depth content research. By emphasizing a content-based strategy that considers the particulars of the user's request as well as the thorough service descriptions provided by the craft owners, our system sets itself apart.

Even with these developments, there are still several obstacles to overcome to create efficient recommendation systems for craft services. These include managing sparse data, precisely capturing the subtleties of user requests, and guaranteeing the accuracy of available information. Subsequent investigations could examine the incorporation of natural language processing methodologies to enhance comprehension of user requirements and the utilization of real-time data to enhance availability matching.

Our study expands on previous work in scheduling, user preference integration, service recommendation techniques, and content-based recommendation systems. Our solution seeks to improve the user experience in service-seeking by adapting to the specific needs of craft services, including availability matching and extensive content analysis. Our system also offers several enhancements over the fuzzy logic-based recommendation system that Hawash et al. [16] suggested. While pairing customers with qualified artisans is the goal of both systems, our method uses TF-IDF for more precise content analysis and real-time availability matching to enhance the relevance and usefulness of recommendations.

The unique way that the suggested work addresses user preferences as well as craft owners' real-time availability is what makes it novel. In contrast to conventional recommendation systems that prioritize static user preferences or broad item-based suggestions, this system incorporates a dynamic availability layer to guarantee that recommendations are in line with the state of the market and the availability of resources. The unique aspect of the suggested work is how specifically it addresses user preferences as well as craft owners' real-time availability. This system incorporates a dynamic layer of availability, ensuring that recommendations are in line with current market conditions and resource availability, in contrast to typical recommendation systems that mostly focus on static user preferences or generalized item-based suggestions.

III. PROBLEM STATEMENT & PROPOSED METHODOLOGY

The primary goal of this system is to locate and schedule skilled artisans more efficiently and effectively based on user preferences and requirements. Clients frequently struggle to find respectable craft entrepreneurs who can provide services when needed. This imbalance results in missed opportunities and angry customers.

The system's specific goals are as follows:

1) Simplifying the Craft Owner Selection Process: We want to make it simpler for customers to locate the best craftsmen for their unique requirements, such as painting, carpentry, moving furniture, plumbing, and electrical work. We do this by utilizing a content-based recommendation system.
2) Improving Customer Satisfaction: More effective service engagements and greater satisfaction rates will result from offering clients tailored recommendations based on thorough problem descriptions and desired availability.
3) Optimising Scheduling for Craft Owners: By matching their availability with client preferences, a system can help craft owners reduce idle hours and increase task fulfillment rates.

To accomplish these goals, our project will apply a methodical strategy that includes multiple essential elements:

A. Text Preprocessing and Important Terms Matching

Important keyword matching and text preparation are essential natural language processing stages that improve recommendation systems' precision and effectiveness. Text preprocessing is the process of normalizing text, eliminating noise, and converting unstructured text into a structured format. By doing this, the data consistency and analytical readiness are guaranteed. Following that, important terms matching locates and retrieves important words or phrases from the processed text and matches them with pertinent profiles or data points. The system may provide exact and relevant recommendations, enhancing user happiness, by precisely matching these phrases.

1) **Text Preprocessing**: To guarantee that the analysis concentrates on the most important parts of the text, stop words and lemmatization are removed from the problem description that the user submits.
2) **Important Term Identification**: Based on the user's problem description, the system will identify important terms about the six crafts (painting, carpentry, plumbing, electrical work, moving furniture, and cleaning). To identify the most pertinent matches, these terms will be compared to the craftsmen's descriptions.

B. Availability Matching

1) **Preferred Days**: The days that the user prefers to receive services are noted and handled.
2) **Craft Owner Availability**: The system determines each craftsman's availability in order to accommodate the user's select days.

C. Similarity Calculation and Ranking

1) **Cosine Similarity and TF-IDF**: To determine the degree of relevance between the service description provided by the craft owner and the problem description provided by the user, the system uses cosine similarity and TF-IDF (Term Frequency-Inverse Document Frequency) vectorization.
2) **Weighted Ranking**: A weighted combination of availability match and description relevancy is used to rank the matched craft owners and produce the final suggestion list.
3) **Models of Similarity**: Three models are used in our technique to determine the similarity:
   a) **Cosine Similarity** Cosine similarity is the most commonly used metric to compare two vectors in the inner product family [17]. Within the text categorization domain, it can be used to indicate how similar two texts are to one another. It takes values from 0 to 1, where 1 represents the texts' complete similarity and 0 indicates no relation

at all. Consequently, we may state the degree of similarity between two texts, *text1* and *text2*, as follows:

$$Sim(text_1, text_2) = \frac{text_1 \cdot text_2}{\| text_1 \| \| text_2 \|} = \frac{\sum_{i=1}^{n} A_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}} \quad (1)$$

where A_i and B_i represent the components of vectors *text1* and *text2*, respectively.

b) **Dot Product Similarity** The dot product similarity is a useful metric to determine how similar two vectors are to one another in a vector space. By calculating the cosine of two vectors' angles, it can ascertain the degree of direction alignment between them. The dot product $\mathbf{A} \cdot \mathbf{B}$ is obtained mathematically by summing the products of the corresponding elements of two vectors $\mathbf{A}$ and $\mathbf{B}$ of the same size n:

$$\mathbf{A} \cdot \mathbf{B} = \sum_{i=1}^{n} A_i \cdot B_i$$

This produces a single scalar number that denotes the similarity; a lower dot product denotes less similarity, while a zero result suggests orthogonality (perpendicularity). The dot product similarity is widely used in computer vision, natural language processing, and machine learning, among other disciplines, when comparing feature vectors or document representations.

c) **Euclidean Similarity** The Euclidean distance is the vector's natural length, or the separation between the point and the origin (Anton, 1993). It is the real separation in m-dimensional space between two points. Its formula can be described as follows:

$$d^E(X, Y) = \sqrt{\frac{\sum_{i=1}^{a} (x_i - y_i)^2}{n}}, n = m \quad (2)$$

where $X = (x_1, x_2, \cdots, x_n)$ and $Y = (y_1, y_2, \cdots, y_m)$
Euclidean distance has been used a lot in time series since it is fast to calculate and has little complexity. Qiang and Vasileios (2007) improved a dimensionality reduction technique for time series analysis by utilizing Euclidean distance, which significantly raised the efficacy and accuracy of similarity searches. A method for matching time series similarity using Euclidean distance was developed by Chen et al. (2015), and its accuracy and efficiency greatly outperformed the other methods. Euclidean distance's worst flaw, though, is that singularities greatly affect it [18].

IV. System Architecture

This section describes the architecture of our content-based recommendation engine for craft owners that is depicted in Figure 1. The system is created using a client/server architecture, which consists of the client side, server side, and database levels. Because each layer serves a specific function, there is a discrete division of labor that makes maintenance, scalability, and future developments easier.

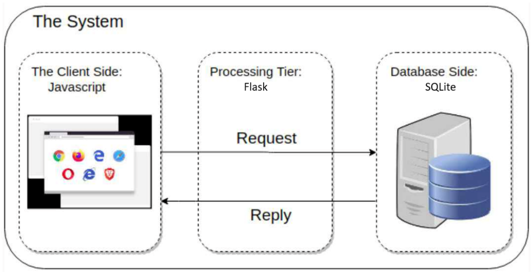

Fig. 1. The architectural design of the tool.

A. Client Side

The client side, which consists of client-side scripts that manage user interaction, represents the system's user interface. Users can access the system and submit requests using online forms via an online interface. The client side handles the traditional request-reply protocol, which is used by the server to reply to requests made by users. The client-side development method uses HTML, CSS, and JavaScript to enable dynamic updates and interactive features.

1) User Interface: Clients can:

1) Submit thorough problem descriptions.
2) Specify desired days and time slots for service.
3) View recommended craft owners depending on their criteria.

2) Form Submission: When a user submits a problem description and preferred availability:

1) The form data is collected and sent to the server.
2) JavaScript is used to validate and process the form data before submission.

B. Server Side

The primary engine driving the program is the server side, which is written in Python using the Flask framework. It enables the backend database and user interface to work together to handle requests from users, process data, and provide dynamic responses, among other necessary tasks.

1) Form Handling and User Input Processing: When a form is submitted:

1) User inputs, such as the preferred availability and problem description, are recorded by the server-side script.
2) Stop words are eliminated and lemmatization is done on the incoming data beforehand.
3) Key words from the user's problem description of the crafts (painting, carpentry, moving furniture, plumbing, and electrical work) are identified.

2) Similarity Calculation: The server processes the input data to calculate similarity scores:

1) The service descriptions provided by craft owners are matched with user descriptions through content-based filtering approaches.
2) Craft owners' availability is compared to user preferences. Craft owners are ranked according to availability and relevance using the combined scores.

C. Database Side

For effective data management and storage, the database side is essential. To hold comprehensive data about users, craft owners, their availability, and service descriptions, the system makes use of a relational database.

The database consists of several tables:

1) **Users Table:** Stores user information including user ID, name, contact details, user type, service type, service ID, description, and rating.
2) **Availability Table:** Contains information about the availability of craft owners, including days and time slots.
3) **Slots Table:** Stores detailed availability slots for each craft owner.
4) **Appointment Table:** Stores detailed records of appointments, including appointment times, dates, user IDs, and craft owner IDs.
5) **Rating Table:** Stores user ratings and reviews for each craft owner, including user IDs, craft owner IDs, ratings, and review comments.
6) **Service Table:** Stores information about the different services offered by craft owners, including service IDs, names, descriptions, and associated craft owner IDs.
7) **Work Table:** Stores records of completed work, including work IDs, user IDs, craft owner IDs, service details, and completion dates.

D. System Workflow

The overall system workflow is as follows:

1) **User Request:** The user submits a problem description and preferred availability through the web interface.
2) **Server Processing:** The server processes the request, pre-processes the input, calculates similarity scores, and matches availability.
3) **Database Interaction:** The server interacts with the database to retrieve craft owner details and availability.
4) **Response Generation:** Based on the processed data, the server generates a list of recommended craft owners and sends it back to the client side.
5) **User Response:** The user views the recommended craft owners and selects the desired one for booking.

The following images show the system in action and provide a greater idea of the user interface and suggestion process. The requirements entered by the user are shown in Figure 2.

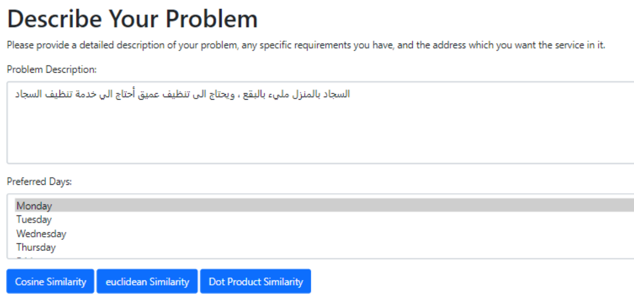

Fig. 2. input needs & select preferred days

Figure 3 depicts the result of the system concerning user needs.

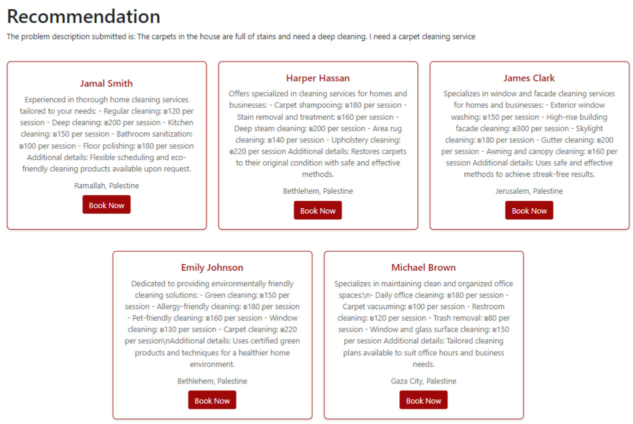

Fig. 3. Results Of Recommendation

Figure 4 depicts the appointment details stored in the Database.

Figure 5 depicts the booked slot not available.

Figure 6 depicts the craft owner profile.

Figure 7 depicts the craft owner managing appointments.

Our system's implementation of this design guarantees the prompt and successful matching of customers with qualified craft owners, improving the entire experience of seeking services.

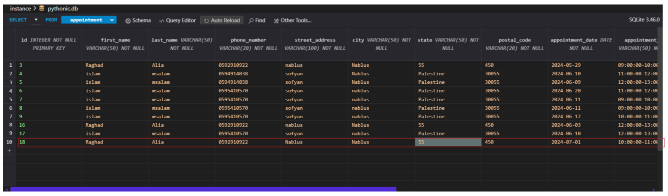

Fig. 4. appointment stored in the Database

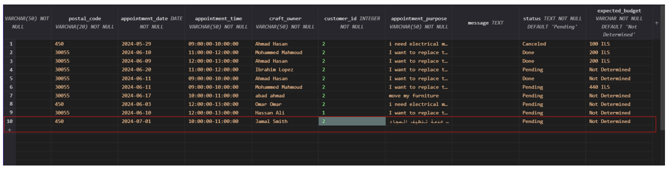

Fig. 5. booked slot is not available

Figure 8 represents the sequence diagram that illustrates the process of asking the system for a proper craftsman.

V. Experimental Tests

To assess the effectiveness of the suggested recommendation system, we ran several tests. The purpose of the tests was to assess how relevant and accurate the system's recommendations were.

A. Dataset

The comprehensive profiles of craft proprietors, including their service descriptions and availability details, made up the dataset used for the tests. Based on typical problem descriptions and preferred service days, user inputs were simulated.

B. Evaluation Metrics

Precision and recall were the assessment measures that were utilized to evaluate the system's performance. Based on user inputs, these metrics provide insights into the system's accuracy in recommending related craft owners.

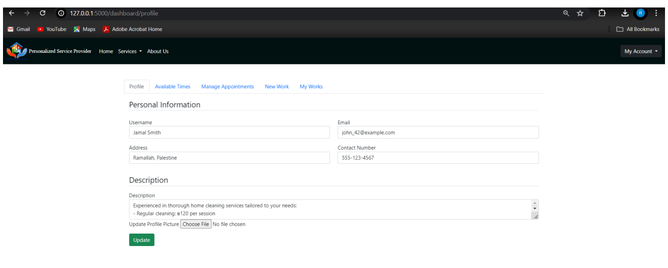

Fig. 6. craft owner profile

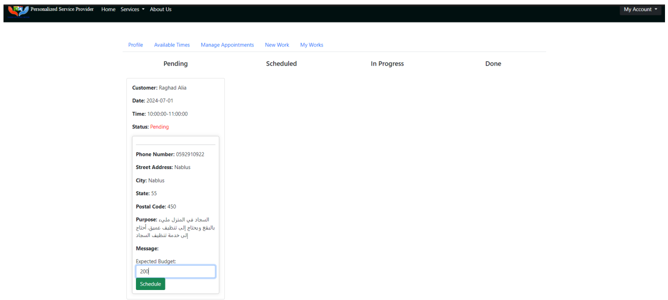

Fig. 7. craft owner manage appointment

C. Results and Discussion

The experiments' outcomes showed that the suggested approach had good recall and precision rates, proving to be useful in making pertinent recommendations. The user experience was further improved by adding availability matching, which ensured the suggested craft owners were available during the user's selected times. 60 persons participated in the test, 26 of them were craftsmen and the others were clients. Table I and Figure 9 show the calculated recall and precision average values of applying cosine similarity to recommend a collection of services.

TABLE I
Cosine Similarity Results

Service	Average Precision	Average Recall
Cleaning	1	1
Carpentry	0.308	0.972
Furniture Moving	0.4734	0.92
Plumbing	0.87	0.5625
Electrical Work	0.2565	0.8337
Painting	0.681	0.879
Overall Average	**0.598**	**0.8612**

Table II and Figure 10 depict the results showing the calculated recall and precision average values of applying Euclidean similarity on the same set of services.

TABLE II
Euclidean Similarity Results

Service	Average Precision	Average Recall
Cleaning	1	1
Carpentry	0.3405	0.977
Furniture Moving	0.4367	0.945
Plumbing	0.87	0.5625
Electrical Work	0.1806	0.95
Painting	0.7704	0.927
Overall Average	**0.5997**	**0.89**

Table III and Figure 11 depict the calculated recall and precision average values of applying dot-product similarity on the same set of services.

To quantify the amount of user satisfaction with the tool, and after using the tool for several days, the test participants

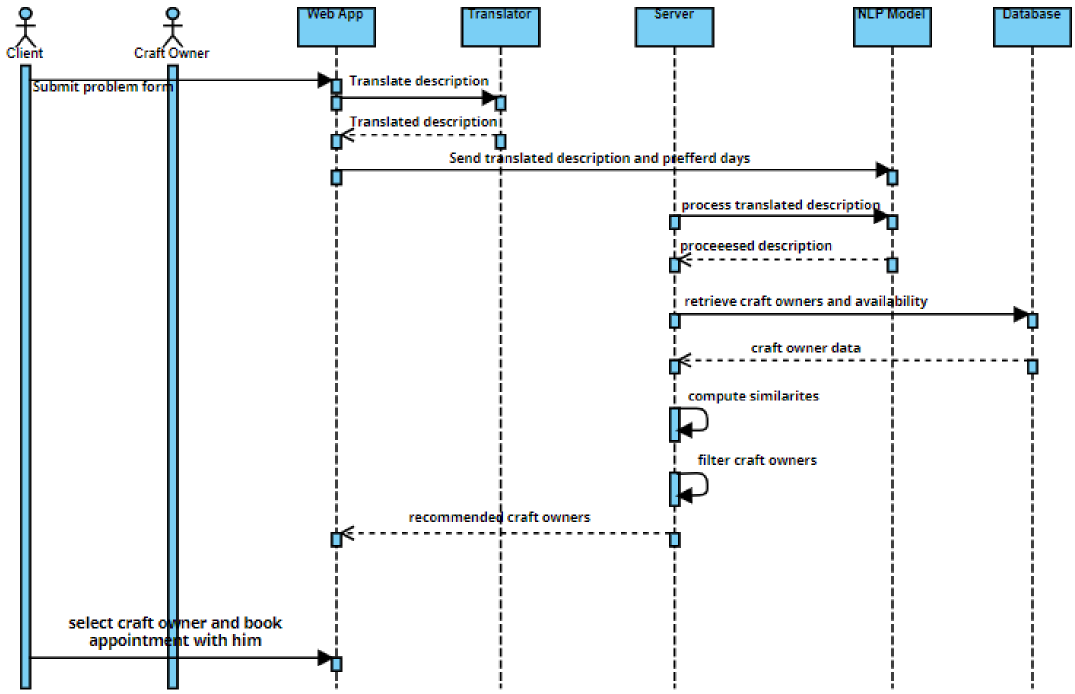

Fig. 8. Sequence diagram for the recommender

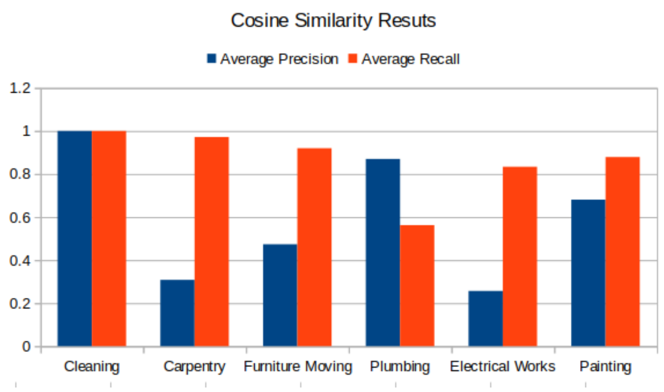

Fig. 9. Cosine Similarity Results.

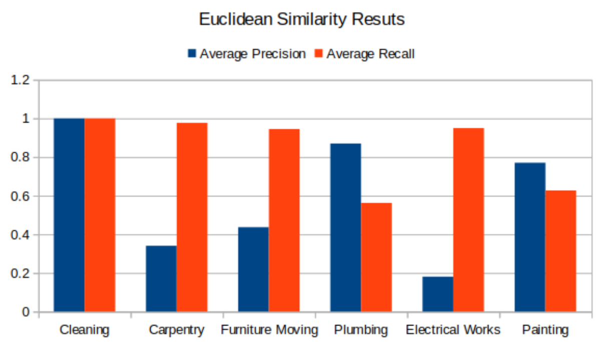

Fig. 10. Euclidean Similarity Results.

TABLE III
DOT PRODUCT SIMILARITY RESULTS

Service	Average Precision	Average Recall
Cleaning	1	1
Carpentry	0.3199	0.904
Furniture Moving	0.2891	0.895
Plumbing	0.87	0.5625
Electrical Work	0.29	0.98
Painting	0.6817	0.905
Overall Average	**0.575**	**0.87**

(34 clients) were asked to fill out a questionnaire that is composed of several questions with scales 1-5 (1:low, 5:high). At the end of the test, we collected the answers of the users:

1) How would you rate the quality of the product/service you received from the craft owner?
2) Did the craft owner meet the specifications you requested?
3) How would you rate your communication with the craft owner?
4) How timely was the response from the craft owner to your inquiries?
5) Did you feel that the craft owner understood your needs?
6) How would you rate the craft owner's ability to meet

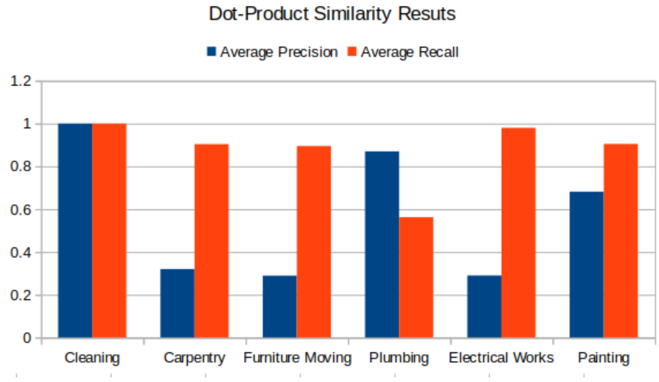

Fig. 11. Dot Product Similarity Results.

the deadline?
7) Was the product delivered on time?
8) How would you rate the value of the money you spent?
9) How satisfied are you with the overall experience?

Table IV reflects the clients' collected answers with percentages of scales.

TABLE IV
PERCENTAGES OF SCALES FOR THE CLIENTS' ANSWERS.

Questions #	Scale 1	Scale 2	Scale 3	Scale 4	Scale 5
Q1	0%	3%	5%	15%	77%
Q2	0%	2%	2%	10%	86%
Q3	1%	0%	5%	12%	82%
Q4	2%	5%	2%	10%	81%
Q5	0%	0%	12%	12%	76%
Q6	0%	0%	0%	25%	75%
Q7	2%	2%	0%	0%	96%
Q8	5%	6%	2%	0%	87%
Q9	1%	0%	5%	0%	94%

VI. Conclusion

A hybrid approach to improve a Content-Based Recommendation System for Craft Owners could combine content-based filtering with collaborative filtering, leveraging user interaction data and availability filtering to refine recommendations. Deep learning techniques, like neural networks, can capture complex patterns in user preferences and item features, predicting preferences more accurately and creating personalized, dynamic recommendations. This approach ensures only available crafts are suggested.

Future work will include additional parameters like cost, ratings, and preferred time windows to enhance the recommendation process. Image processing techniques will allow clients to upload photographs of their issues, enabling the system to recommend appropriate craft owners through visual analysis, benefiting those with limited problem descriptions or user involvement.

Moreover, A hybrid approach combining content-based filtering with collaborative filtering can improve a Content-Based Recommendation System for Craft Owners. This uses user interaction data and availability filtering to refine recommendations. Deep learning techniques, like neural collaborative filtering or autoencoders, can predict user preferences more accurately, creating personalized recommendations. These will be in our plans.

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