A User-centric System for Improving Human-Computer Interaction through Fuzzy Logic-based Assistive Messages

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Abstract: The fast growth of the internet and communication technology in recent years has resulted in rendering computers easily accessible to everyone. However, people have different knowledge and characteristics that can affect their ability to use computers and at the same time create barriers to achieve an effective user experience. The reason for this is to provide dynamic adaptability to users' individual needs. In view of this compelling need, this paper presents a user-centric system that seeks mainly to improve the interaction of users with the software they use. To achieve this, the system employs fuzzy logic to model the computer knowledge of users and based on this classification, it delivers assistive messages, which are pertinent to the interaction with the system. These messages are tailored to the user groups that have been created, as well as the degree of detail which is more adequate for each group. As a testbed for our research, the presented approach has been incorporated in a learning management system to support tutors towards having a better experience while interacting with this software. The system has been evaluated by users during the COVID-19 lockdown with promising results.

1 INTRODUCTION

The proliferation of the internet and communication technology (ICT) in recent years has brought significant changes in many parts of people's daily lives. These changes rendered the technology an indispensable tool to better organize their time, communicate with others, learn, make purchases, make bookings for places of entertainment or means of travel, etc. As such, different software or web sites are being used by many people around the world, who are different in terms of their needs, preferences and computer skills (Krouska et al., 2020 (a)). Thus, adapting these systems to a diverse audience is a significant notion that can improve human-computer interaction (HCI) (Papakostas et al., 2021). In order to provide a personalized interaction route for each different user, current approaches involve improving and modifying sotware content, feedback, novigation support, etc. (Troussas et al., 2021).

Adaptive software has great interactivity affordances, because it delivers a user-centered experience increasing user engagement. The delivery of assistive messages and feedback to users is an integral component of it (Wang et al., 2019). For more qualitative interaction, assistive messages can be facilitated by sophisticated techniques towards delivering appropriate assistance to users, when needed (Zadeh Kashani and Hamidzadeh, 2020). The more adaptive the messages are to the users' needs, the more effective and accurate they are. For instance, when interacting with a software, if users has a high level of computer skills and knowledge, it is useless or even tiring for them to receive a huge volume of messages; in this sense, their experience may be unpleasant.

Based on reviews of the relevant scientific literature (Bhanuse and Mal, 2021; Suhaim and Berri, 2021), it appears that the research on the delivery of assistive messages to users is still in its early stages. Several academics have investigated the delivery of

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assistive messages in various environments, including:

- e-learning (Soulef et al., 2021; Tahir et al., 2021; Krouska et al., 2020 (b); Wan and Niu, 2020; Qomariyah and Fajar, 2019);
- e-commerce (Peng et al., 2020; Zhao, 2019; Chauhan et al., 2019; Ouaftouh et al., 2019);
- e-travel and smart tourism sites (Fararni et al., 2021; Chaudhari and Thakkar, 2020; Hassannia et al., 2019);
- e-health systems (Ferretto et al., 2020; Tellería et al., 2020; Gräßer et al., 2016);
- online movies systems (Singla et al., 2020; Deldjoo et al., 2019; Troussas et al., 2018);
- search engines (Peña et al., 2020; Ahmedi and Shabani, 2017).

In the aforementioned research efforts, the authors employed, among others, semantic approaches, collaborative filtering, content-based filtering, genetic algorithms and machine learning to deliver adaptive assistive messages to users.

In view of the above, this article presents a user-centric system that aims to boost users' engagement with the software they use. Hence, the system employs fuzzy logic to represent users' computer expertise and, based on this classification, sends out helpful messages that are relevant to their engagement with the system. These messages are customized to the user groups that have been formed, as well as the level of detail that each group requires. The offered method has been implemented into a learning management system as a testbed for our study in order to assist instructors in having a better experience when engaging with this software.

The remainder of this paper is organized as follows. Section 2 presents the fuzzy weights, being used to model users' computer knowledge. In Section 3, the rules for the delivery of assistive messages are described. Section 4 presents the experimental results and discussion. Finally, Section 5 continues with the work's conclusions and recommendations for further research activities.

2 FUZZY WEIGHTS FOR MODELING COMPUTER KNOWLEDGE

The improvement of HCI and the delivery of a pleasant user experience involves mostly the consideration of the users' computer knowledge (Nie et al., 2021; Khodr et al., 2020; Méndez et al., 2019; Wynn and Hult, 2019). Nonetheless, determining the users' computer knowledge level is a difficult task, riddled with ambiguity. For example, a user with a score of 92/100 in a computer proficiency test cannot be classified as exceptional or very good. Both states include some truth. Fuzzy logic may be the answer in such uncertain situations. In our case, the Computer Tech Skills Practice Test was used[1].

In this study, four fuzzy weights, namely Novice (N), Intermediate (I), Good (G) and Expert (E), are used to represent the computer knowledge level of users of any kind of software. Trapezoidal membership functions are used to express each fuzzy weight. These functions are represented by four boundary values: the degree of membership grows from 0 to 1 between a1 and a2, flattens between a2 and a3, and then drops from 1 to 0 between a3 and a4. Each category of computer knowledge level has an interval when users' scores fully belong to the category, and this is why trapezoidal membership functions were employed. The following equations illustrate the fuzzy weights membership functions, where x is the student score; while Fig. 1 depicts their scheme:

$$\mu_n(x) = \begin{cases} 1 & x \leq 30 \\ 1 - \dfrac{x-30}{10} & 30 < x < 40 \\ 0 & x \geq 40 \end{cases}$$

$$\mu_i(x) = \begin{cases} \dfrac{x-30}{10} & 30 < x < 40 \\ 1 & 40 \leq x \leq 60 \\ 1 - \dfrac{x-60}{10} & 60 < x < 70 \\ 0 & x \leq 30 \text{ or } x \geq 70 \end{cases}$$

$$\mu_g(x) = \begin{cases} \dfrac{x-60}{10} & 60 < x < 70 \\ 1 & 70 \leq x \leq 80 \\ 1 - \dfrac{x-80}{10} & 80 < x < 90 \\ 0 & x \leq 60 \text{ or } x \geq 90 \end{cases}$$

$$\mu_e(x) = \begin{cases} \dfrac{x-80}{10} & 80 < x < 90 \\ 1 & 90 \leq x \leq 100 \\ 0 & x \leq 80 \end{cases}$$

[1] https://www.tests.com/practice/computer-skills-practice-test

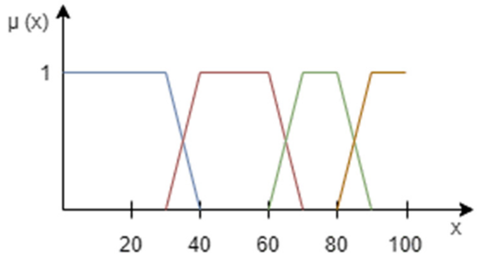

Figure 1: Scheme of fuzzy weights membership functions.

In light of the foregoing, the four fuzzy weights are utilized to portray users' computer knowledge level. The values of these fuzzy weights, which range from 0 to 1, are defined using the aforementioned membership functions. Thereby, the equation $\mu_n(x) + \mu_i(x) + \mu_g(x) + \mu_e(x) = 1$ is correct.

Ten faculty members from Greek public institutions defined the fuzzy weights and thresholds of their membership functions. In more detail, the faculty members were requested to describe the computer knowledge levels of users during the whole educational process, as well as the intervals of a user's degree of success, characterizing each of these computer knowledge levels. The faculty members have more than 10 years of expertise in instructing computing in university settings and can vouch for an error-free portrayal of users' knowledge levels.

3 RULES FOR ASSISTIVE MESSAGES DELIVERY

This section describes the rules that are associated with the four fuzzy weights explained earlier for determining the quantity and detail of the assistive messages that should be provided to each user. Each user will be delivered these messages to be helped while navigating in the software based on the fuzzy weight s/he belongs to.

The detail and quantity of assistive messages varies. These rules were established by the same 15 professors who specialize in teaching computing. Particularly, they are given the seven derived categories of membership in the above-described fuzzy weights, and they are asked their opinion about the number and detail of messages that are required for helping users belonging to different computer knowledge level categories. Then, the average of their answers is taken into consideration for the formation of the rules. The whole set of the rules are presented in Table 1. Table 1 depicts the number and the complexity degree of the learning activities for each instance of the fuzzy weights, namely the number and detail of assistive messages that a particular user will receive based on his/her computer knowledge level. Note that d is the detail degree of the message that can take values from 1 (of low detail) to 3 (of high detail).

Table 1: Rules for assistive messages based on fuzzy weights.

Fuzzy weights	Assistive messages (with degrees of detail and quantity)
μ_n=1	3 of d=3 2 of d=2 0 of d=1
$\mu_n > \mu_i$	2 of d=3 3 of d=2 0 of d=1
μ_i=1 or $\mu_i > \mu_n$	2 of d=3 2 of d=2 1 of d=1
$\mu_i > \mu_g$	1 of d=3 3 of d=2 1 of d=1
μ_g=1 or $\mu_g > \mu_i$	1 of d=3 2 of d=2 2 of d=1
$\mu_g > \mu_e$	0 of d=3 2 of d=2 3 of d=1
μ_e=1	0 of d=3 1 of d=2 4 of d=1

It needs to be underlined that the assistive messages are pertinent to the screen the user sees. For each screen, the messages are different and according to the fuzzy weights. The software delivers five messages per screen; this number is adequate so that the user can be informed but not in a tedious way. However, this number can be changed based on the kind of software in which this approach is incorporated. Following, several examples of assistive messages of an educational software are given based on users' computer knowledge level vector (μ_n, μ_i, μ_g, μ_e):

- A user with computer knowledge (1, 0, 0, 0) who want to create an announcement will get more detailed messages, such as "To upload an announcement to students, firstly you should write the title and the body text, and then select if the students receive it in their emails. The Date Ends field is to declare for how much time the announcement will be visible.". Whereas a user with computer knowledge (0, 0, 0, 1) will get less detailed messages on the same subject, such as "To upload an announcement to students, enter the title, body text, email delivery and date ends option.”.

- A user with computer knowledge (0, 0.2, 0.8, 0) will get more detailed messages, such as: “You can upload an xml file with your course questions. Next, select ‘Introduction from IMS QTI’ to enter these questions in your course Test Bank. Then, you can modify them according to your needs.”. Whereas a user with computer knowledge (0, 0, 0, 1) will get less detailed messages on the same subject, such as “Upload the xml file with course questions, select ‘Introduction from IMS QTI’ and modify the questions if needed.”.

4 EXPERIMENTAL RESULTS AND DISCUSSION

The software must always be evaluated to determine its effectiveness and user acceptance. During the COVID-19 pandemic, special emphasis has been placed on the imposed asynchronous and online education. As such, we have incorporated the presented approach in a learning management system that was used by faculty members of public universities in the capital city of the country to support the online education.

The evaluation process took place in two parallel phases during the lockdown of the spring semester of the academic year 2019-2020:

- Phase 1: 20 Faculty members used the learning management system that provided static assistive messages to them which are the same for every user.
- Phase 2: 20 Faculty members used the learning management system that provided the fuzzy logic-based assistive messages (our presented approach).

For the evaluation, the faculty members of Phases 1 and 2 were asked three questions about their experience with the system. After that, the results of the questions posed to Faculty members of Phase 2 are presented, as well as t-test was employed to assess the effectiveness of the assistive messages that is achieved with the use of the presented system (through fuzzy logic) in comparison to its conventional version (static messages). The questions are in a five-point Likert scale from -2 (absolutely disagree) to 2 (absolutely agree) and are the following:

- Were the assistive messages helpful? (Q1)
- Did the assistive messages improve your interaction with the system? (Q2)
- Were the assistive messages adjusted to your computer knowledge level? (Q3)

The results of the above questions for Phase 2 were aggregated and are shown in three pie charts (Fig. 2-4).

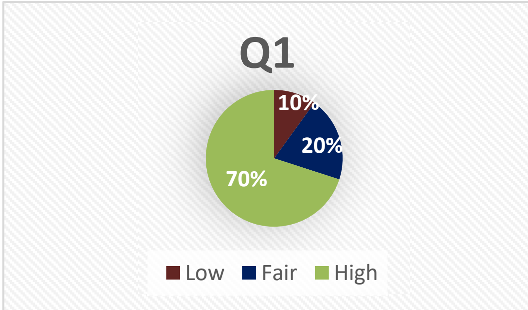

Figure 2: Pie chart for Q1.

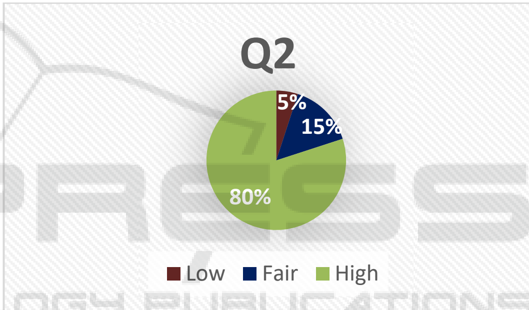

Figure 3: Pie chart for Q2.

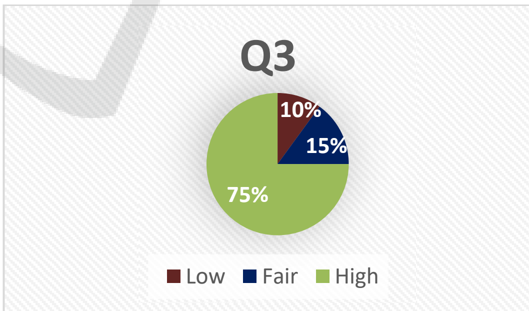

Figure 4: Pie chart for Q3.

Concerning the first question (Q1), 14 faculty members (a percentage of 70%) declared that the assistive messages were helpful. Furthermore, 16 faculty members (a percentage of 80%) stated that the assistive messages improved your interaction with the system. Also, 15 faculty members (a percentage of 76%) confirmed that the assistive messages were adjusted to your computer knowledge level. These results were anticipated given that the assistive messages using fuzzy logic improved the interaction of people with the software, offering them an optimized user experience.

Furthermore, t-test was employed on the results of questions (Q1, Q2, Q3) posed to faculty members in Phase 1 and 2, to compare the presented approach (with assistive messages using fuzzy logic) with the conventional approach (with static assistive messages, same for all users). The alpha value, for the experiment, was set to 0.05, and we discovered that there is a statistically significant difference between the means of the two trials for Q1, Q2, and Q3, by evaluating the p-values (Table 2).

Table 2: T-test results.

	Q1		Q2		Q3	
	Phase 1	Phase 2	Phase 1	Phase 2	Phase 1	Phase 2
Mean	-0,3	1,45	-0,25	1,7	-0,55	1,55
Variance	0,536842	0,997368	1,25	0,536842	1,313158	0,892105
Observations	20	20	20	20	20	20
Hypothesized Mean Difference	0,767105		0,893421		1,102632	
df	0		0		0	
t Stat	38		38		38	
P(T<=t) one-tail	-6,31845		-6,52389		-6,32418	
t Critical one-tail	1,04E-07		5,46E-08		1,02E-07	
P(T<=t) two-tail	1,685954		1,685954		1,685954	
t Critical two-tail	2,08E-07		1,09E-07		2,05E-07	

Analyzing the results of the t-test, it can be inferred that our presented approach for assistive messages offered a better experience to the users. The reason is because the assistive messages found to be helpful for the users (Q1), improved their interaction with the system (Q2) and were adjusted to their computer knowledge level (Q3).

5 CONCLUSIONS

This paper presents a user-centric approach to enhance the interaction between humans and computers. To achieve this, it supports the delivery of adaptive and assistive messages to users, when needed. Since the computer knowledge plays a significant role for HCI, in this paper, it is modelled using fuzzy weights to figure out the level to which each user belongs. Moreover, in this research, several rules have been constructed, considering the fuzzy weights (as created using fuzzy logic) and the detail of the assistive messages (meant to be achieved); these rules are employed by the system and are delivered to users, when appropriate. As a testbed for this research, the presented approach has been incorporated in an e-learning software to help instructors create a pedagogically sound learning environment during the COVID-19 lockdown period. The experimental results are very promising, showing that the users are helped by the presented approach and have a good experience during the interaction with the software.

It needs to be noted that this approach can be incorporated in any kind of software, e.g. e-commerce, e-health systems etc., if the messages are properly altered. Future research steps include the incorporation of this approach into other kind of software and its evaluation to measure the effectiveness of the assistive messages in other domains as well.

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