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METHODOLOGIES AND APPLICATION

A zSlices-based general type-2 fuzzy logic system for users-centric adaptive learning in large-scale e-learning platforms

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Abstract Sophisticated educational technologies are evolving rapidly, and online courses are becoming more easily available, generating interest in innovating lightweight data-driven adaptive approaches that foster responsive teaching and improving the overall learning experience. However, in most existing adaptive educational systems, the black-box modeling of learner and instructional models based on the views of a few designers or experts tended to drive the adaptation of learning content. However, different sources of uncertainty could affect these views, including how accurately the proposed adaptive educational methods actually assess student responses and the corresponding uncertainties associated with how students receive and comprehend the resulting instruction. E-learning environments contain high levels of linguistic uncertainties, whereby students can interpret and act on the same terms, words, or methods (e.g., course difficulty, length of study time, or preferred learning style) in various ways according to varying levels of motivation, pre-knowledge, cognition, and future plans. Thus, one adaptive instructional model does not fit the needs of all students. Basing the instruction model on determining learners' interactions within the learning environment in interpretable and easily read white-box models is crucial for adapting the model to students' needs and understanding how learning is realized. This paper presents a new zSlices-based type-2 fuzzy-logic-based system that can learn students' preferred knowledge delivery needs based on their characteristics and current levels of knowledge to generate an adaptive learning environment. We have evaluated the proposed system's efficiency through various large-scale, real-world experiments involving 1871 students from King Abdulaziz University. These experiments demonstrate the proposed zSlices type-2 fuzzy-logic-based system's capability for handling linguistic uncertainties to produce better performance, particularly in terms of enhanced student performance and improved success rates compared with interval type-2 fuzzy logic, type-1 fuzzy systems, adaptive, instructor-led systems, and non-adaptive systems.

Keywords Type-2 fuzzy logic systems · E-learning · Intelligent learning environments

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1 Introduction

The primary objective of any educational or training system is to achieve the maximum value out of learning resources for learners. Within a classroom, teachers may find it difficult to evaluate the capabilities of learners accurately. This kind of evaluation often encompasses knowledge, interest, background, and motivation. By considering these variables, teachers are able to redefine and shift the teaching space to fit the requirements of each student. As all different learners have their own way of gaining knowledge and needs, teachers should take these dissimilarities into account if they want students to be successful by readjusting the instructional approaches to their needs. The smaller the number of students, the more time a teacher can spend thinking about these variables to offer student-centered education (James 2012). If contrasted directly with group learning, one-on-one teaching and training improves student successes more significantly (Bloom 1984; Kidd 2010; Vandewaetere et al. 2011). However, it is difficult to offer this kind of adaptive learning in standard teaching spaces.

The internet has become a central core to the educative environment experienced by learners, thus facilitating learning in any location and at any time (Zhao and Wan 2006). This kind of e-learning usually features a computer and the network-facilitated exchange of skills and information. According to Allen and Seaman (2008), almost a quarter of all higher and further education students were training via online-only courses in 2008. In 2009, Ambient Insight Research (2009) stated that 44 % of higher education pupils in the USA took at least one online course, and predicted that this would rise to 81 % within five years. In addition, there are over 30 million online students enrolled in at least one higher education class. Over half of all these pupils live in the USA, where close to 16.1 million pupils took at least one internet class in 2011 and 1.5 million took all of their classes online. It is predicted that this figure will rise to around 4.1 million in 2016 (Ambient Insight Research 2009). These statistics, throughout the world and in the USA, are indicative of the speedy and universal embrace of e-learning, moving it from a burgeoning substitute to a conventional teaching method. E-learning is now quickly entering mainstream education and becoming a leading method of higher education instruction (Ambient Insight Research 2009).

However, it seems that e-learning courses struggle with the same kinds of issues seen in conventional classes and particular ones resulting from a deficit of valuable communication between students and teachers (Ciloglugil and Inceoglu 2012; Essalmi et al. 2010). Furthermore, e-learning resources are essentially provided to and created for a huge number of students, and they do not take students' unique requirements or capabilities into consideration (Ciloglugil and Inceoglu 2012; Essalmi et al. 2010). These issues led to degraded pupil outcomes and a lower level of learning satisfaction and success, which have, in turn, resulted in the emergence of adaptive e-learning environments (James 2012). Student needs in the teaching environment can be classified by many variables, such as student knowledge, learning style, affective states, personality traits, and student goals (Ciloglugil and Inceoglu 2012). The main objective of considering these variables is to allow students to better achieve their learning goals and objectives (Martins et al. 2008). Course content could be adaptive to each learner through feedback, contents sequencing, and the presentation of the materials (Shute and Zapata-Rivera 2012). The efficiency of adaptive educational systems depends on the methodology employed to collect information regarding the learning needs of students as well as on how this information is processed to develop a personalized learning context (Shute and Zapata-Rivera 2012).

Existing online learning environments face several sources of uncertainty. For example, how do we ensure higher accuracy in evaluating the students' knowledge level and other aspects to provide the best individual adaptive teaching? This question is quite critical due to several sources of uncertainty in how accurately students' responses are evaluated by adaptive educational methods as well as the corresponding uncertainties related to how the provided instruction is received and understood by the learner. Within e-learning environments, there are high levels of linguistic uncertainty, as students can vary widely in their interpretation of the same terms, words, or methods (e.g., course difficulty, length of study time). These variances are related to students' experiences, motivation, knowledge, and future plans about learning a given subject in an e-learning environment (Ahmad et al. 2004). To tackle the uncertainty that may hinder the development of an improved learning context, it is advised that any adaptive educational system should incorporate a flexible artificial intelligence (AI) technique (Ahmad et al. 2004).

However, the majority of the current techniques (e.g., Bayesian networks, hidden Markov models, neural networks) are hampered by the issue of knowledge representation, as such AI techniques cannot create transparent models of human behavior. Thus, it is not possible to rely on the black-box characteristics of these AI techniques because they pose significant challenges to users with regard to interpretation (Stathacopoulou et al. 2007). Another potential limitation of such black-box, model-based techniques is that they involve time-consuming iterative learning procedures to adapt their models as a result of the dynamic nature of the e-learning process (Idris et al. 2009). Nevertheless, the majority of the employed AI approaches do not learn from user behaviors to adapt themselves or to create easily read and understood white-box models that can handle high levels of uncertainty.

Fuzzy logic systems (FLSs) are well known for their ability to generate white-box models that can handle high levels of uncertainty. However, the vast majority of FLSs employ type-1 FLSs that handle the encountered uncertainties based on precise type-1 fuzzy sets (Mendel 2001). In contrast, interval type-2 FLSs can handle the uncertainties faced through interval type-2 fuzzy sets characterized by a footprint of uncertainty (FOU), which provides an extra degree of freedom for handling high uncertainty levels (Mendel 2001; Lynch et al. 2006). Previous work has shown that interval type -2 FLSs are capable of providing better performance when compared to type-1 FLSs with similar number of rules; this has been caused by the notion that interval type-2 fuzzy sets can better handle the encountered uncertainties (Mendel 2001; Hagras 2004). During the even distribution of uncertainty by interval type-2 fuzzy sets across the FOU, it is customary to anticipate improvement with regard to modeling precision and performance when using general type-2 fuzzy sets, thus allowing for an unbalanced distribution within applications in areas that have uneven distributions of uncertainty when information regarding this kind of distribution is available (Wagner and Hagras 2010).

In this paper, we present a new zSlices type-2 fuzzy-logic-based system that can identify the learners' preferred learning strategies and knowledge delivery needs based on the characteristics of learners and their existing knowledge levels in generating an adaptive learning atmosphere. The efficiency of the proposed system has been assessed via the use of a number of "real-world" tests that involved 1,871 students from King Abdulaziz University. These tests are indicative of the proposed zSlices type-2 FLS's capability to deal with linguistic uncertainties to produce high levels of student achievement, particularly with regard to suitable levels of completion and improved learning outcomes. The proposed system outperformed the non-adaptive systems; adaptive system versions are led by the instructor, with type-1 based FLSs and interval type-2 FLSs.

The rest of the paper is structured as follows. The following section provides a brief overview of some AI techniques employed for adaptive educational systems; then, the subsequent two sections give an overview of type-2 fuzzy logic systems and of the application of fuzzy logic systems to education and e-learning platforms. Section 5 presents our proposed zSlices-based type-2 fuzzy-logic-based system for users-centric adaptive learning in large-scale e-learning platforms. Section 6 presents the experiments and results, while both our conclusions and our future work are discussed in Sect. 7.

2 Overview of AI techniques for adaptive educational systems

The aim of adaptive educational systems is to tailor the overall learning approach in order to fulfill the needs of students (Essalmi et al. 2010). Hence, it is essential that the profiles of students be created accurately with consideration for the examination of their affective states, levels of knowledge, skills, and personality traits. The information required then needs to be utilized and developed in order to improve the adaptive learning environment (Essalmi et al. 2010). Acquiring those learning data models then can be used in two ways, prescribed pedagogy proposed by the experts and the designers of the adaptive educational system or by the dynamically learning suited the pedagogy from the teachers or amateurs student's behaviors. This learning capabilities will ensure the improvements of the learner and the system over life-long learning mode. Hence, AI approaches are regarded as valuable tools, as they have the ability to develop and replicate the decision-making process adopted by people (Frias-Martinez et al. 2004).

There are various AI techniques that have been used in adaptive educational systems, such as fuzzy logic (FL), Bayesian networks, neural networks, and hidden Markov models. There are various ways through which AI approaches are used in adaptive educational systems. For example, in some systems, the core focus is to examine and assess student characteristics to generate profiles of the students with the intention of evaluating their overall level of knowledge to be used as basis for prescribed software pedagogy (Yadav et al. 2014; Yildiz and Baba 2014; Millán et al. 2013; Chen and Li 2013; Sripan and Suksawat 2010; Bai and Chen 2008; Venkatesan and Fragomeni 2008; Yannibelli et al. 2006; Yeh and Lo 2005; Gertner and VanLehn 2000). The AI approaches are also used to facilitate the diagnostic process completion so that course content can be adjusted to cater to the needs of every student, and some of them are used to learn from the student behaviors to adjust the prescribed software pedagogy (Idris et al. 2009; Cha et al. 2006; Gutierrez-Santos et al. 2010; Moreno et al. 2005; Seridi-Bouchelaghem et al. 2005; Xu et al. 2002; Huang et al. 2007; Kavčič 2004; Hsieh et al. 2012).

Nevertheless, the majority of the employed adaptive educational systems do not learn from user behaviors (learns to adapt) to create easily read and understood white-box models that could handle high levels of uncertainties and are easily understood and checked by the lay user. However, in the case of the majority of the used techniques (e.g., Bayesian networks, hidden Markov models, and neural networks), there is an issue with knowledge representation, which means that such AI techniques cannot create transparent models of human behavior. Thus, it is not possible to rely on the black-box characteristics of these AI techniques, as they pose significant challenges to users regarding interpretation (Stathacopoulou et al. 2007). Another potential limitation of such black-box model-based techniques is that they need to repeat time-consuming iterative learning procedures in order to adapt their models as a result of the dynamic and constantly changing nature of the e-learning process.

3 zSlices general type-2 fuzzy logic systems

The formation of a zSlice occurs when a general Type-2 Fuzzy set is sliced within the third dimension (z) at z_i level. The slicing action causes interval set within the third dimension containing high z_i (Wagner and Hagras 2010).

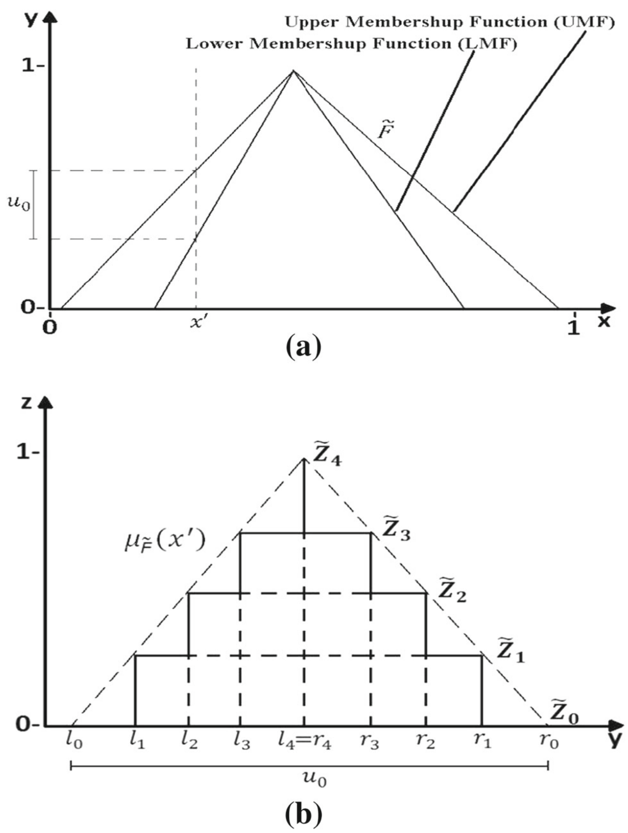

Fig. 1 **a** Front view of a general type-2 fuzzy set; **b** third dimension at x' of a zSlices-based general type-2 fuzzy set (Wagner and Hagras 2010)

Importantly, a zSlice $\tilde{Z}_i$ s equal to an "interval type-2 fuzzy set" except that the membership level $\mu_{\tilde{Z}_i(x,u)}$ within the third dimension is not fixed to 1, rather is equivalent to z_i whereby $0 \leq z_i \leq 1$. Therefore, the zSlice $\tilde{Z}_i$ equation could be denoted as indicated below (Wagner and Hagras 2010):

$$\tilde{Z}_i = \int_{x \in X} \int_{u_i \in J_{i_x}} z_i / (x, u_i) \tag{1}$$

where at every value of x (as illustrated by Fig. 1a), a set of interval containing height z_i alongside domain J_{i_x} ranging between l_i and r_i is created through z-slicing, as illustrated in Fig. 1b, $0 \leq i \leq I$ and I denote the zSlices quantity (excluding z_0), whereas $z_i = i/I$ (Wagner and Hagras 2010).

Additionally, Wagner and Hagras (2010):

$$\tilde{Z}_0 = \int_{x \in X} \int_{u_i \in J_{i_x}} 0/(x, u_i) \tag{2}$$

where $\tilde{Z}_0$ is seen as a unique case with $z = 0$. In particular, the focus would be $1 \leq i \leq I$, because $\tilde{Z}_0$ would not support the "crisp output" for the zSlice-based type-2 fuzzy logic structure; thus, it may be discarded without any effects (Wagner and Hagras 2010). A general type-2 fuzzy set $\tilde{F}$ is equal to an infinite zSlices quantity obtained:

$$\tilde{F} = \int_{0 \leq i \leq I} \tilde{Z}_i \quad 1 \rightarrow \infty \tag{3}$$

In a discrete universe of discourse, Eq. (3) may be simplified as Wagner and Hagras (2010):

$$\tilde{F} = \sum_{0 \leq i \leq I}^{I} \tilde{Z}_i \tag{4}$$

A description for the zSlice-based general type-2 fuzzy set operations that includes the union and intersection operations undertaken via joining and meeting operations, in addition to descriptive details regarding zSlices T2FLS functions, is presented in Wagner and Hagras (2010).

4 Fuzzy logic systems in education and e-learning platforms

A FLS can be implemented to facilitate the formation of a summary of students' preferences pertaining to knowledge acquisition and understanding (Ahmad et al. 2004). A framework geared toward user modeling, based on the FLS, induces simplified reasoning for both users and designers, which therefore assists in terms of amendments and comprehension (Ahmad et al. 2004; Jameson 1996; Kavčič et al. 2003). Furthermore, FLSs are commonly utilized in order to examine and assess learning and knowledge-related outcomes (Yadav et al. 2014; Yildiz and Baba 2014; Millán et al. 2013; Chen and Li 2013; Sripan and Suksawat 2010; Bai and Chen 2008; Venkatesan and Fragomeni 2008; Prokhorov and Kulikovskikh 2015). The FLS are also used to facilitate the diagnostic process completion, known as student modeling, so that course content can be adjusted to cater to the needs of every student. In relation to Xu et al. (2002), a profiling system adopting a multi-agent approach has been presented, whereby the creation of fuzzy models for content and students was based on a dynamic plan formally defined ahead of time for one individual (Xu et al. 2002). This framework was obtained through profile abstraction, which is recognized as comprising student-centered learning tasks, such as the topic at hand and the time spent on the topic (Xu et al. 2002). Furthermore, the content framework was devised and created with fuzzy links between the subjects, and the knowledge of the individuals (referred to as prerequisite relations) was established to be utilized in order to formally determine the learning adaptation (i.e., the order of issues to be examined by the individual) (Xu et al. 2002).

The work of Kavčič (2004) employs FL to model user knowledge of domain concepts. The work represents the dependencies between domain concepts to cycle graph, as some concepts have essential or supportive perquisites between them, and they use fixed rules to accomplish dynamic updating of user knowledge regarding the concepts. Through these procedures, the right concepts are adapted to the students (Kavčič 2004). Similarly, the work of Chrysafiadi and Virvou (2015) developed the use of fuzzy knowledge states (FuzKSD) in a way that points out the alterations on the state of a student's level of knowledge. Chrysafiadi and Virvou (2015) also uses a fuzzy cognitive map(FCM), which collaborates with FuzKSD and represents the relationship between the domain concepts. When changes to the learner's level of knowledge of domain concepts arise, FuzKSD tries to point out the learner's knowledge and update it in both this concept and all other concepts that are related to it, considering the learner's updated knowledge as well as the dependencies in FCM regarding the domain concepts (Chrysafiadi and Virvou 2015).

Additionally, Hsieh et al. (2012) proposed a system which uses fuzzy inference to help with the analysis of the learners' linguistic ability through accumulated learner profile which helps them to select the best article that is to be read next. Once the learner has gone through the article, he/she is challenged through vocabulary tests which involve words that he/she has encountered while reading that article (Hsieh et al. 2012). Thereafter, the learners profile is updated in relation to their performance in the test as well as their linguistic ability which is recalculated and analyzed, and finally, a new article is chosen for delivery (Hsieh et al. 2012).

Nevertheless, in previous research, the behaviors of the students are reformed through criterion links between student knowledge and topics with the individual behavior being restricted by establishing a dynamically grounded study plan for the student. However, the needs of the student in previous studies were not learned automatically through a large dataset obtained from various students, as was the case with the system discussed in this thesis. Moreover, the systems considered in previous studies did not adapt in a lifelong learning approach to ensure that the generated models adapt to the students' changing needs and expanding knowledge. Moreover, to the best of our knowledge, the adoption of type-2 fuzzy approaches in the context of an adaptive learning educational environment has not been examined yet in the literature.

5 The proposed zSlices-based type-2 fuzzy logic system for users-centric adaptive learning in large-scale e-learning platforms

Our proposed theoretical and practical environment based on zSlices general type-2 fuzzy logic aims to correlate and learn various needed instructional variables like the suited current level of content difficulty and the time needed for the taught content that can tackle the current state of various learner variables, such as current levels of knowledge and characteristics. Figure 2 shows an overview of the proposed environment where interactions occur between various learners and the e-learning environments in the application layer. The main objective of this layer is first to specify needed instructional variables to be learned (the outputs) in the learning environment according to the learners' variables, which are the inputs. Secondly, this layer will enable the system to gather and monitor these specified data related to evaluating students' understanding of their knowledge delivery needs according to their characteristics variables in the online learning environment, which is subsequently examined and analyzed in the learning fuzzy rules layer.

The learning fuzzy rules' functionality generates the system learned rules. The objective of the first component of this layer is to extract the zSlices general type-2 fuzzy sets for the system input and output, which are based on a method that centers on creating type-2 fuzzy sets (Liu and Mendel 2007; Almohammadi et al. 2014; Almohammadi and Hagras 2013; Almohammadi et al. 2015) gathered from a sample of participants ($n = 30$ students in the conducted experiments) to handle the internal uncertainties for two groups of students. After acquiring the fuzzy sets and collecting data (which took one week in the conducted experiments), the system is able to generate the fuzzy rules that describe the best needed instructional actions that satisfy the current state of students' capabilities and characteristics. The proposed zSlices system utilizes supervised one-pass technique [(inspired by previous studies Bilgin et al. (2012), Wang (2003), Hagras et al. (2007), Almohammadi and Hagras (2013)] for extracting the rules from the collected data in this extracting fuzzy rule component.

Finally, the adaptation layer is used when it takes the students' learning current input states and gives them suitable outputs to accomplish their learning tasks. Our proposed environment in this layer further enables the online adaptation and enhancement of rules, and facilitates long-term learning due to changes in performance and capabilities, delivery instructional needs. The proposed environment comprises the three following layers (as shown in Fig. 2), which with their sub-components are discussed in detail in the following subsections.

5.1 Application layer

The main purpose of this layer is to specify the learners' variables, which are the inputs according to the system outputs. This process is related to the content or instructional variables to be learned. Instructional variables could include the suitable learning content difficulty level, time needed, and preferred learning style to acquire knowledge and to promote student learning. This should match the current learner variables, which are the students' current level of knowledge and

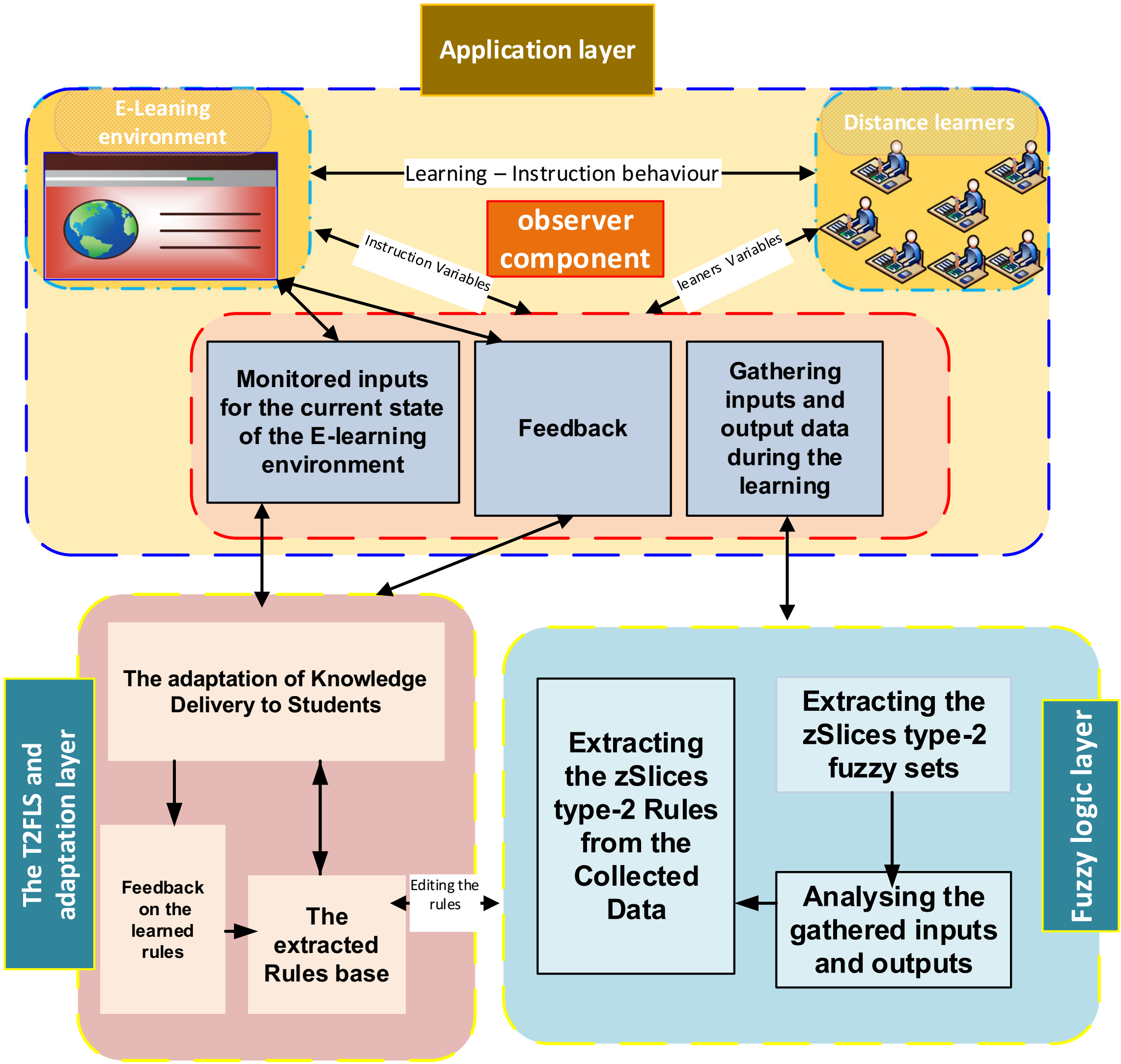

Fig. 2 An overview on the proposed zSlices based on type-2 fuzzy logic for users-centric adaptive learning system in large-scale e-learning platforms

other personal characteristics to particularize and personalize the adaptation process.

5.1.1 The observer component

The objective of this component in the proposed system is to record and monitor the system inputs and outputs. The data are captured via the collection and assessment of various student knowledge delivery requirements (outputs for the fuzzy system) according to their characteristics and capabilities (inputs for the fuzzy system) within the application layer. It is noteworthy that this component is also responsible for actively recording data (both current inputs and outputs) to see whether there is any change in the student instructional needs in accordance with the current state of the e-learning environment (Hagras et al. 2007; Almohammadi and Hagras 2013). Therefore, the observer component enables proposed environments to create and learn a descriptive model of the appropriate student instructional needs used in handling and promoting the students' current levels of knowledge and capability; this is accomplished via this process of data gathering, which generates a set of multi-input and multi-output data pairs, which will be formed as follows (Bilgin et al. 2012; Wang 2003; Hagras et al. 2007; Hagras 2007; Hagras et al. 2008):

$$x^{(t)}; y^{(t)} \quad (t = 1, 2, \ldots, N)\,, \tag{5}$$

where N is the total number of data instances, $x^{(t)} \in R^n$, and $y^{(t)} \in R^k$. The rules generated by the proposed system are basically explaining how the k output, which is the students' instructional needs variables $y = (y_1, \ldots, y_k)^T$, is affected by the input variables $x = (x_1, \ldots, x_n)^T$, which are the student characteristics and capabilities. A correlating model for inputs to outputs is constructed using the established fuzzy rules without requiring a mathematical model. Thus, individual rules can be adapted online, affecting only certain aspects of the descriptive model created and learned by the proposed system.

5.2 The fuzzy rules learning layer

5.2.1 Extracting the zSlice-based type-2 fuzzy sets

Categorization of the gathered learning-instruction behavior input/output data via the relevant fuzzy membership functions is an important step in the fuzzy rule learning layer. This component enables the system to quantify the raw input and output values by changing them into linguistic labels such as *very low*,*low*,*moderate*,*high*, and *very high* for the average level of knowledge in the current learning subject. As explained in Sect. 3, a zSlice $\tilde{Z}_i$ is equivalent to an interval type-2 fuzzy set with the exception that its membership grade $\mu_{\tilde{Z}_i(x,u)}$ in the third dimension is not fixed to 1; instead, it is equal to z_l, where $0 \leq z_i \leq 1$ (Wagner and Hagras 2010). Interval type-2 fuzzy sets with the height z_l extraction approach that produce a type-2 fuzzy set are detailed in Liu and Mendel (2007), Almohammadi et al. (2014), Almohammadi and Hagras (2013), Almohammadi et al. (2015). Their FOU integrates the numerous type-1 fuzzy sets that describe the interpretation of each students' views regarding a particular linguistic label that justifies the learned instructional and learner variables (inputs–outputs) related to the learning environment.

Accordingly, the learners' various perspectives regarding modeling these words would be embedded by the generated FOU to handle uncertainties for the type-2 fuzzy sets. In this approach, the data are collected by asking the students for their views regarding their specific linguistic labels through which type-1 fuzzy sets would be generated. Following this step, the type-2 fuzzy sets are extracted while the type-1 fuzzy sets representing the learners' individual views are combined, resulting in the FOU of the type-2 fuzzy sets being delivered that represent the given word (Liu and Mendel 2007; Almohammadi et al. 2014; Almohammadi and Hagras 2013; Almohammadi et al. 2015). Through the application of the representation theorem, each of the interval type-2 fuzzy sets $\tilde{A}_s$ can be computed as follows:

$$\tilde{A}_s = \bigcup_{i=1}^{n} A^i \tag{6}$$

where A^i is referred to as the ith combined type-1 fuzzy set and $\cup$ is an aggregation operation. Reckoning the upper membership function (MF) $\bar{\mu}_{\tilde{A}}(x)$ and the lower MF $\underline{\mu}_{\tilde{A}}(x)$ of $\tilde{A}_s$ can deliver the process of $\tilde{A}$ production (Liu and Mendel 2007; Almohammadi et al. 2014; Almohammadi and Hagras 2013; Almohammadi et al. 2015). This depends on the shape of the embedded type-1 fuzzy sets and the FOU model to be generated for $\tilde{A}_s$. In our system, we use the interior FOU models and the right and left shoulder MFs for the upper and lower MF parameters, as shown in Fig. 3a–c. As is shown in

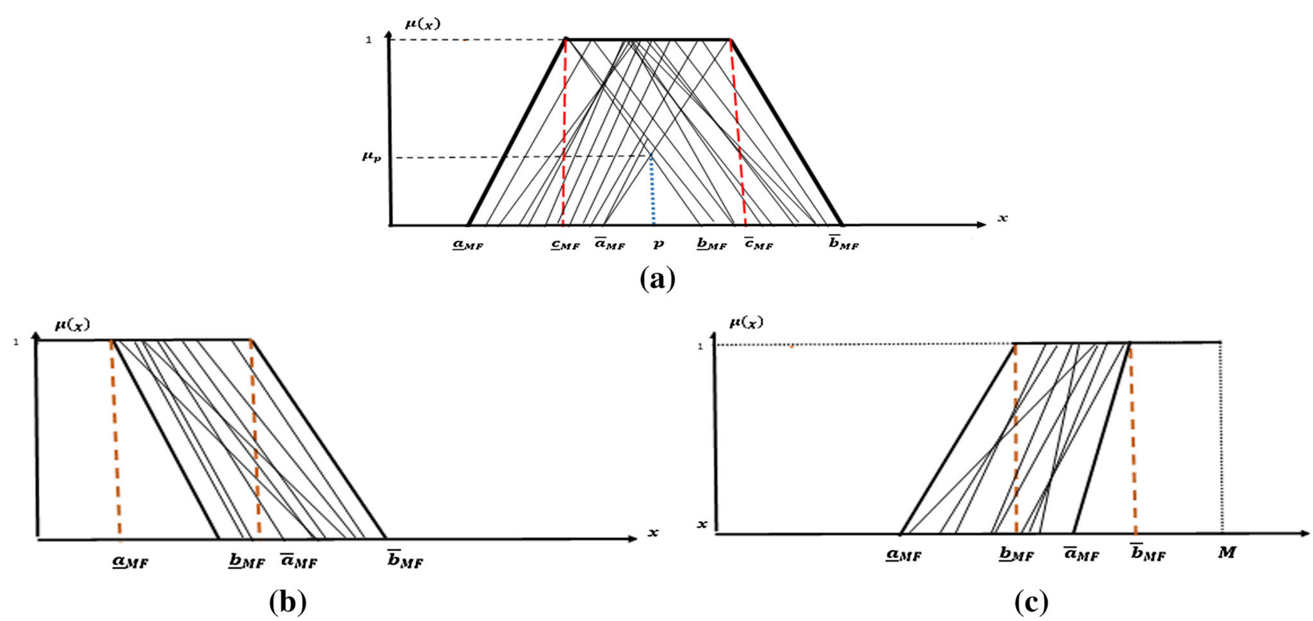

Fig. 3 **a** An interior type-2 MF embedding the different type-1 fuzzy sets, **b** left shoulder type-2 MF embedding the different type-1 fuzzy sets, **c** right shoulder type-2 MF embedding the different type-1 fuzzy sets (Liu and Mendel 2007; Almohammadi et al. 2014; Almohammadi and Hagras 2013; Almohammadi et al. 2015)

Fig. 3a, the resulting interior interval type-2 fuzzy set is constructed by the parameters $\underline{a}_{\mathrm{MF}}$, $\underline{c}_{\mathrm{MF}}$, $\bar{c}_{\mathrm{MF}}$, and $\bar{b}_{\mathrm{MF}}$ denoting a trapezoidal upper MF and the parameters $\bar{a}_{\mathrm{MF}}$ and $\underline{b}_{\mathrm{MF}}$ for a symmetric triangular lower MF, with an intersection point (p, μ_p). We describe the procedures for calculating these parameters below.

Given the parameters for the symmetric triangle type-1 MFs generated for each of the i students $[a^i_{\mathrm{MF}}, b^i_{\mathrm{MF}}]$, for interior FOUs, we provide the procedure for calculating the FOU model below (Liu and Mendel 2007; Almohammadi et al. 2014; Almohammadi and Hagras 2013; Almohammadi et al. 2015).

For the upper MF $\bar{\mu}_{\tilde{A}}(x)$, we need to follow these three steps:

1. For $\mu(x) = 0$, find $\underline{a}_{\mathrm{MF}}$ to be equal to the minimum $a^{\min}_{\mathrm{MF}}$ of all left-end points a^i_{MF} and $\bar{b}_{\mathrm{MF}}$ to be equal to the maximum $b^{\max}_{\mathrm{MF}}$ of all right-end points b^i_{MF}.
2. For $\mu(x) = 1$, find $\underline{c}_{\mathrm{MF}}$, $\bar{c}_{\mathrm{MF}}$ that correspond to the minimum and the maximum of the centers of the type-1 MFs.
3. Approximate the upper MF$\bar{\mu}_{\tilde{A}}(x)$ by connecting the following points with straight lines: $(\underline{a}_{\mathrm{MF}}, 0)$, $(\underline{c}_{\mathrm{MF}}, 1)$, $(\bar{c}_{\mathrm{MF}}, 1)$, and $(\bar{b}_{\mathrm{MF}}, 0)$.

Figure 3a shows the result, which is a trapezoidal upper MF. For the lower MF$\underline{\mu}_{\tilde{A}}(x)$, we need to follow these three steps (Liu and Mendel (2007); Almohammadi et al. (2014); Almohammadi and Hagras (2013); Almohammadi et al. (2015)):

1. For $\mu(x) = 0$, find $\bar{a}_{\mathrm{MF}}$ to be equal to the maximum $a^{\max}_{\mathrm{MF}}$ of all left-end points a^i_{MF} and $\bar{b}_{\mathrm{MF}}$ to be equal to the minimum $b^{\min}_{\mathrm{MF}}$ of all right-end points b^i_{MF}.
2. Compute the intersection point (p, μ_p) by using the following equations (Liu and Mendel 2007):

$$p = \frac{(\underline{b}_{\mathrm{MF}} - \bar{a}_{\mathrm{MF}}) + \bar{a}_{\mathrm{MF}}(\underline{b}_{\mathrm{MF}} - \underline{c}_{\mathrm{MF}})}{(\bar{c}_{\mathrm{MF}} - \bar{a}_{\mathrm{MF}}) + (\underline{b}_{\mathrm{MF}} - \underline{c}_{\mathrm{MF}})} \tag{7}$$

$$\mu_p = \frac{(\underline{b}_{\mathrm{MF}} - p)}{(\underline{b}_{\mathrm{MF}} - \underline{c}_{\mathrm{MF}})} \tag{8}$$

3. Approximate the lower MF $\underline{\mu}_{\tilde{A}_s}(x)$ by connecting the following points with straight lines: $(\underline{a}_{\mathrm{MF}}, 0)$, $(\bar{a}_{\mathrm{MF}}, 0)$, $(p, \mu(p))$, $(\underline{b}_{\mathrm{MF}}, 0)$, and $(\bar{b}_{\mathrm{MF}}, 0)$.

The result, as it is illustrated in Fig. 3a, is a triangle lower MF.

The method adopted for computing the FOU for the right and left shoulders is similar to that described in Liu and Mendel (2007), Almohammadi et al. (2014), Almohammadi and Hagras (2013), Almohammadi et al. (2015) . To compute the upper MF $\bar{\mu}_{\tilde{A}}(x)$ for the left shoulder (as shown in Fig. 3b), points (0, 1), $(\bar{a}_{\mathrm{MF}}, 1)$, and $(\bar{b}_{\mathrm{MF}}, 0)$ should be joined with straight lines. To compute the lower MF$\underline{\mu}_{\tilde{A}}(x)$, points (0, 1), $(\underline{a}_{\mathrm{MF}}, 1)$, $(\underline{b}_{\mathrm{MF}}, 0)$, and $(\bar{b}_{\mathrm{MF}}, 0)$ should be connected with straight lines. Similarly, as shown in Fig. 3c, to estimate MF $\bar{\mu}_{\tilde{A}}(x)$ for the right shoulder, points $(\underline{a}_{\mathrm{MF}}, 0)$, $(\underline{b}_{\mathrm{MF}}, 1)$, and $(M, 1)$ should be joined with straight lines. To approximate the lower MF$\underline{\mu}_{\tilde{A}}(x)$, points $(\underline{a}_{\mathrm{MF}}, 0)$, $(\bar{a}_{\mathrm{MF}}, 0)$,

Fig. 4 Main interface of the designed online learning platform

$(\bar{a}_{\mathrm{MF}}, 1)$, and $(M, 1)$ should be joined with straight lines (Liu and Mendel 2007; Almohammadi et al. 2014; Almohammadi and Hagras 2013; Almohammadi et al. 2015).

The experiments section describes and draws the zSlices general type-2 fuzzy set combining two interval type-2 fuzzy sets with height z_2 from two categorized participant groups.

5.2.2 *Extracting the fuzzy rules*

The extracted fuzzy set is amalgamated with the collected input/output user data with the aim of obtaining those rules known to define student behaviors. Our system's method of learning the rules from the data is based on an extended and further developed version of the Mendel–Wang approach (Bilgin et al. 2012; Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013). This is a one-pass technique for extracting fuzzy rules from the accumulated data. The fuzzy sets for the antecedents and consequents of the rules divide the input and output space into fuzzy regions. Several multi-input/multi-output rules are extracted using the type-2 fuzzy system, through which the association between $x = (x_1, \ldots, x_n)^T$ and $y = (y_1, \ldots, y_k)^T$ can be explained such that:

$$IF\, x_1 \text{is } \tilde{A}_1^l \ldots \text{ and } x_n \text{ is } \tilde{A}_n^l \text{ THEN } y_1 is\ \tilde{B}_1^l \ldots \text{and } y_k\ is\ \tilde{B}_k^l \quad (9)$$

$l = 1, 2, \ldots, M$, where l is the index of the rules and M is the number of rules.

Fig. 5 Learning units designed for both Excel and PowerPoint

Specifically, for each input x_s where $s = 1, 2, \ldots, n$, there are V_i type-2 fuzzy sets $\tilde{A}_s^q, q = 1, \ldots, V_i$, and each one of them has defined I zSlices $\widetilde{Z_l A_s^q}$ where $l = 1, \ldots, l$. Similarly, for each output y_c, there are V_o type-2 fuzzy sets $\tilde{B}_c^h, h = 1, \ldots, V_o$, where $c = 1, 2, \ldots, k$, and each set has defined I zSlices $\widetilde{Z_l B_c^h}$, where $l = 1, \ldots, l$. It is worth noting

Fig. 6 Main lesson interface

Fig. 7 Text-based explanation interface for the pie chart creation lesson

that the total number of zSlices is the same for all the V_i input sets and V_o output sets, which are generated according to the various students' views, as indicated in the previous section.

To clarify and summarize the following representation, an approach comprising a single output is illustrated because of the method's simplicity for upgrading the rules involving multiple outputs. We note the several phases included in this rule extraction below.

Phase 1 The upper and lower membership values are calculated as $\bar{\mu}_{\tilde{A}_s^q}(x_s^{(t)})$ and $\underline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)$ for each zSlice $\widetilde{Z_l A_s^q}$, where $l = 1, \ldots, l$, for each of the fuzzy set $\tilde{A}_s^q, q = 1, \ldots, V_i$ and for each input variable s $(s = 1, \ldots, n)$ regarding a fixed input–output pair $(x^{(t)}; y^{(t)})$ in the dataset $(t = 1, 2, \ldots, N)$ by finding $q^* \in \{1, \ldots, V_i\}$ such that (Bilgin et al. 2012; Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013):

$$\mu^{zcg}_{\tilde{A}_s^{q^*}}\left(x_s^{(t)}\right) \geq \mu^{zcg}_{\tilde{A}_s^q}\left(x_s^{(t)}\right) \tag{10}$$

For all $q = 1, \ldots, V_i$, $\mu^{zcg}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)$ is the z-weighted center of gravity of the membership of $\tilde{A}_s^q$ at $x_s^{(t)}$, which can be seen below (Bilgin et al. 2012; Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013):

$$\mu^{zcg}_{\tilde{A}_s^{q^*}}\left(x_s^{(t)}\right) = \frac{1}{2}\left[\frac{\sum_l^I \bar{\mu}_{\widetilde{Z_l A_s^q}}\left(x_s^{(t)}\right) * z_l}{\sum_l^I z_l} + \frac{\sum_l^I \underline{\mu}_{\widetilde{Z_l A_s^q}}\left(x_s^{(t)}\right) * z_l}{\sum_l^I z_l}\right] \tag{11}$$

where $z_l = l/I$ and $1 \leq l \leq I$ .The rule given below is generated by $(x^{(t)}; y^{(t)})$ (Bilgin et al. 2012; Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013):

$$\text{IF } x_1 \text{ is } \tilde{A}_1^{q^{*(t)}} \text{ and } x_n \text{ is } \tilde{A}_n^{q^{*(t)}} \text{ THEN centered } at\ y^{(t_u^l)} \tag{12}$$

For all of the input variables x_s, there are V_i type-2 fuzzy sets $\tilde{A}_s^q$, which makes the greater amount of possible rules equal to V_i^n. However, when considering the dataset, there will be the generation of those rules among the V_i^n possibilities that show a dominant region comprising a minimum of one data point.

In the first phase, there is the generation of one rule for each particular input/output data pair, with the selected fuzzy set being that which is seen to obtain the greatest value of membership at the data point and particularly selected as the

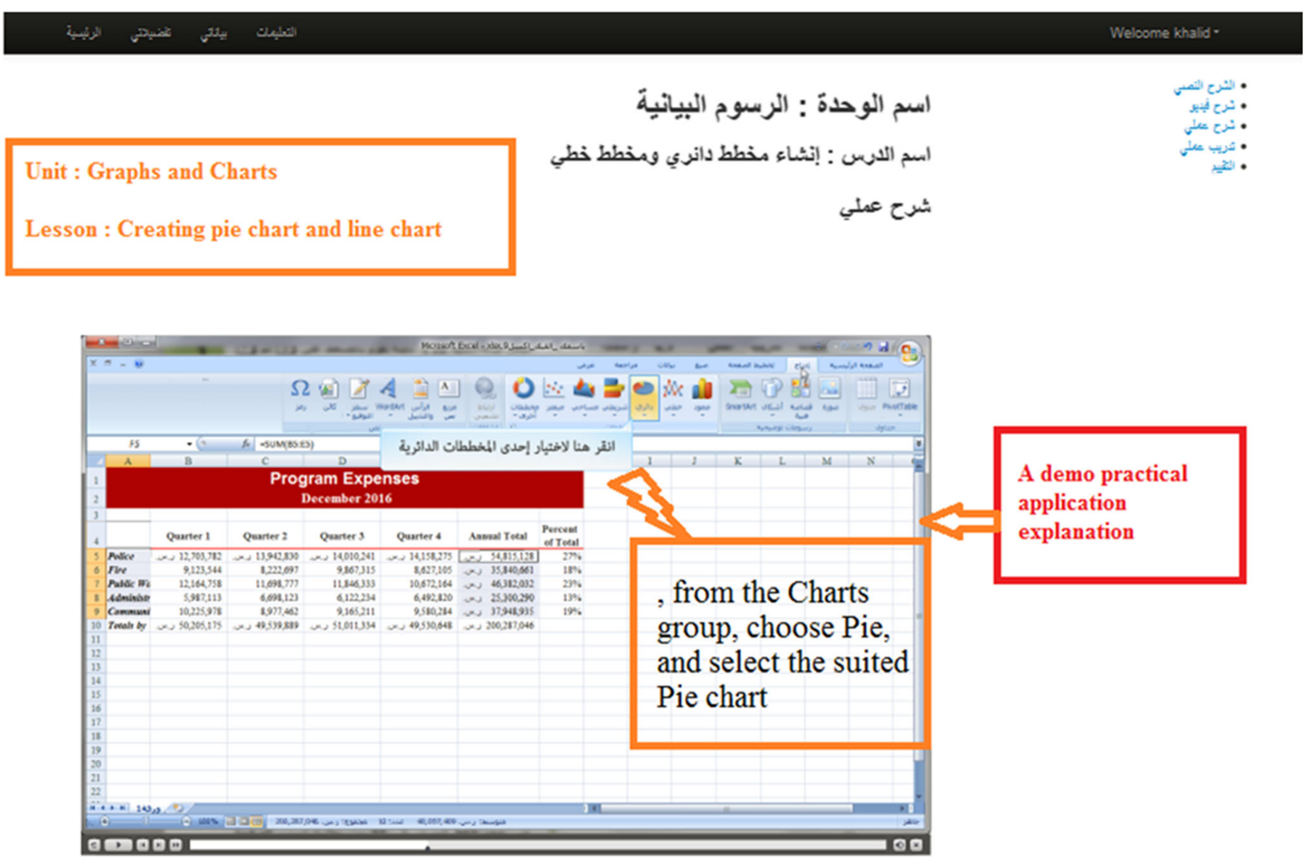

Fig. 8 Practical demonstration on how to create a pie chart

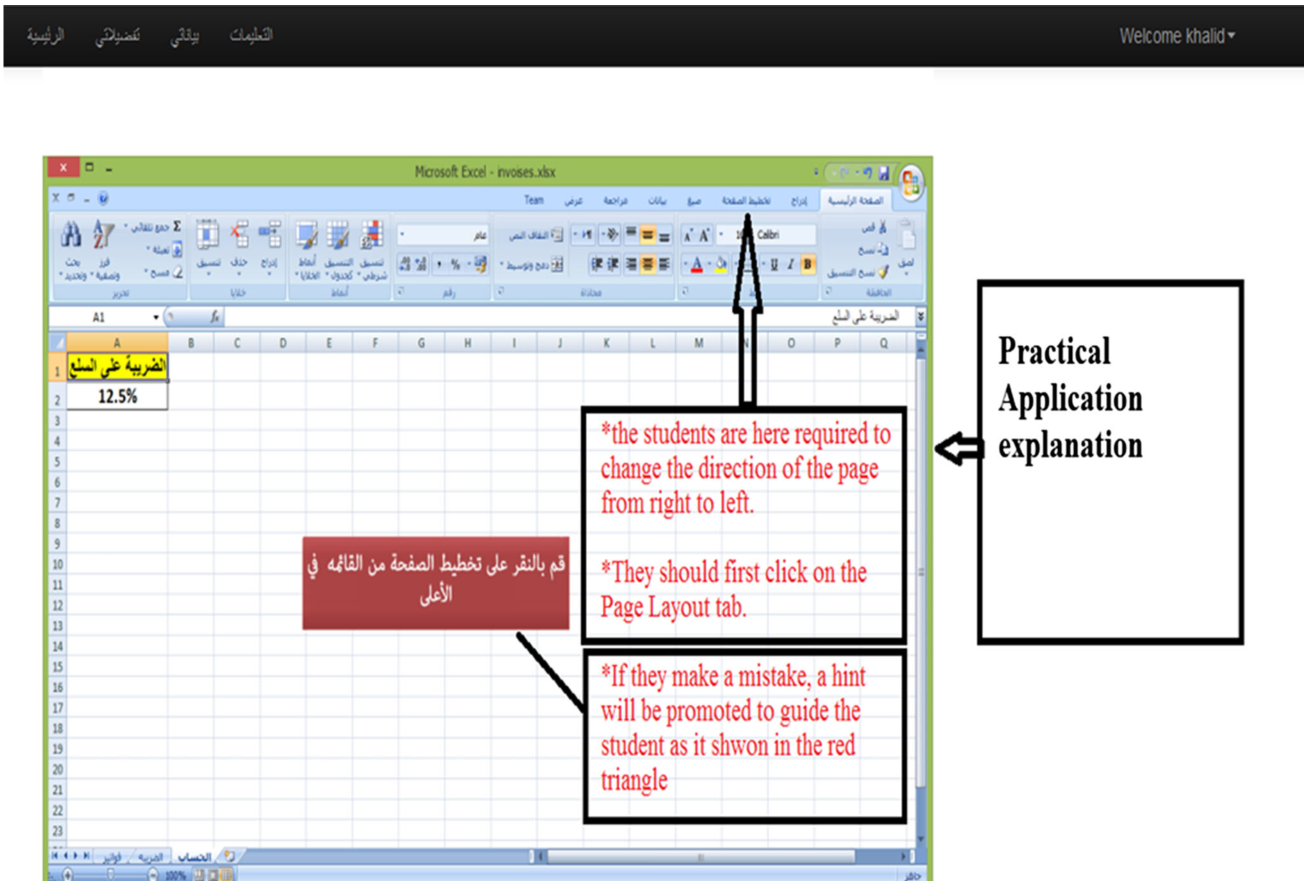

Fig. 9 Practical exercise showing the steps for changing the chart direction (when students respond incorrectly)

one in the rule's IF element. However, this is not the final version of the rule, which is computed in the following step. The calculation of the rule weight is accomplished as follows (Bilgin et al. 2012; Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013):

$$wi^{(t)} = \prod_{s=1}^{n} \mu^{zcg}_{\tilde{A}_s^{q*}} \left(x_s^{(t)} \right) \tag{13}$$

A rule $wi^{(t)}$ weight is a degree of the strength of the points $x^{(t)}$ regarding the fuzzy region covered by the entire rule.

Phase 2 For all of the data points from 1 to N, the first phase is repeated. With the help of this practice, N rules extracted from the data are taken in the form of Eq. (12). Phase 1 witnesses the generation of multiple rules, all of which have the same IF part in common yet are all conflicting. During this phase, those rules that have the same IF part are amalgamated to form a single rule. Subsequently, the rules are divided into groups, with rules in each group seem to have the same IF part. If such groups amount to M and it may also be stated that the group has rules, then (Bilgin et al. 2012; Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013):

$$\text{IF} x_1 \text{ is } \tilde{A}_1^l \ldots \text{ and } x_n \text{is } \tilde{A}_n^l \text{ THEN } y \text{ is centered } at \;\; y^{(t_u^l)} \tag{14}$$

where $u = 1, \ldots, N$ and t_u^l are the data points index of Group l. The equation given below shows how to calculate the weighted average of all rules involved in the conflict group:

$$av^{(l)} = \frac{\sum_{u=1}^{N_l} y^{(t_u^l)} wi^{(t_u^l)}}{\sum_{u=1}^{N_l} wi^{(t_u^l)}} \tag{15}$$

Subsequently, a single rule is formed by integrating these N_l rules, resulting in the following form (Bilgin et al. 2012; Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013):

$$\text{IF} x_1 \text{is } \tilde{A}_1^l \ldots \text{ and } x_n \text{is } \tilde{A}_n^l \text{ THEN } y \text{ is } \tilde{B}^l \tag{16}$$

where there is the selection of the output fuzzy set $\tilde{B}^l$ on the basis of the following: We compute the lower and the upper membership values $\underline{\mu}_{\widetilde{Z_l \tilde{B}_c^h}} \left(av^{(l)} \right)$ and $\bar{\mu}_{\widetilde{Z_l \tilde{B}_c^h}} \left(av^{(l)} \right)$ for each zSlice $\widetilde{ZB}_c^h$, where $l = 1, \ldots, I$ for each fuzzy output $\tilde{B}^l, \ldots, \tilde{B}^{V_o}$; calculate B^{h*} such that (Bilgin et al.

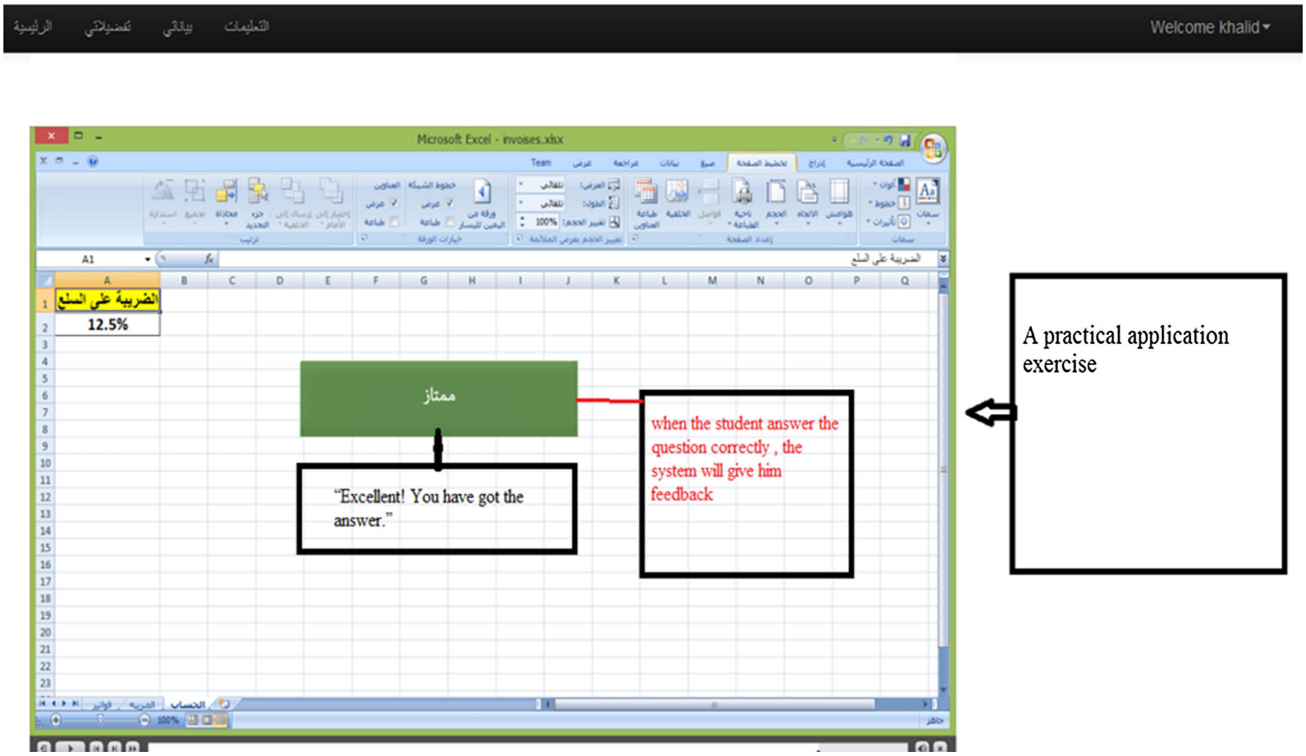

Fig. 10 Practical exercise showing the steps for changing the chart direction (when students respond correctly)

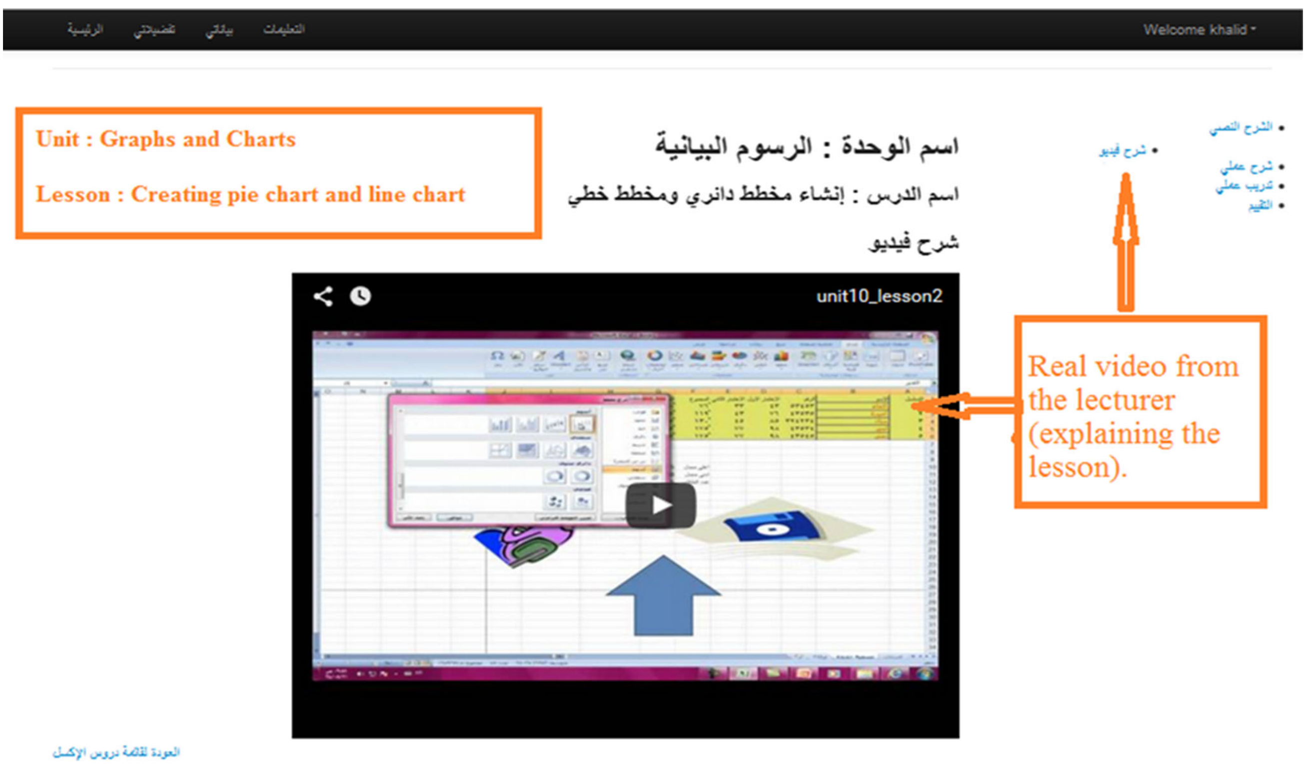

Fig. 11 Lecturer video interface for creating the pie chart lesson

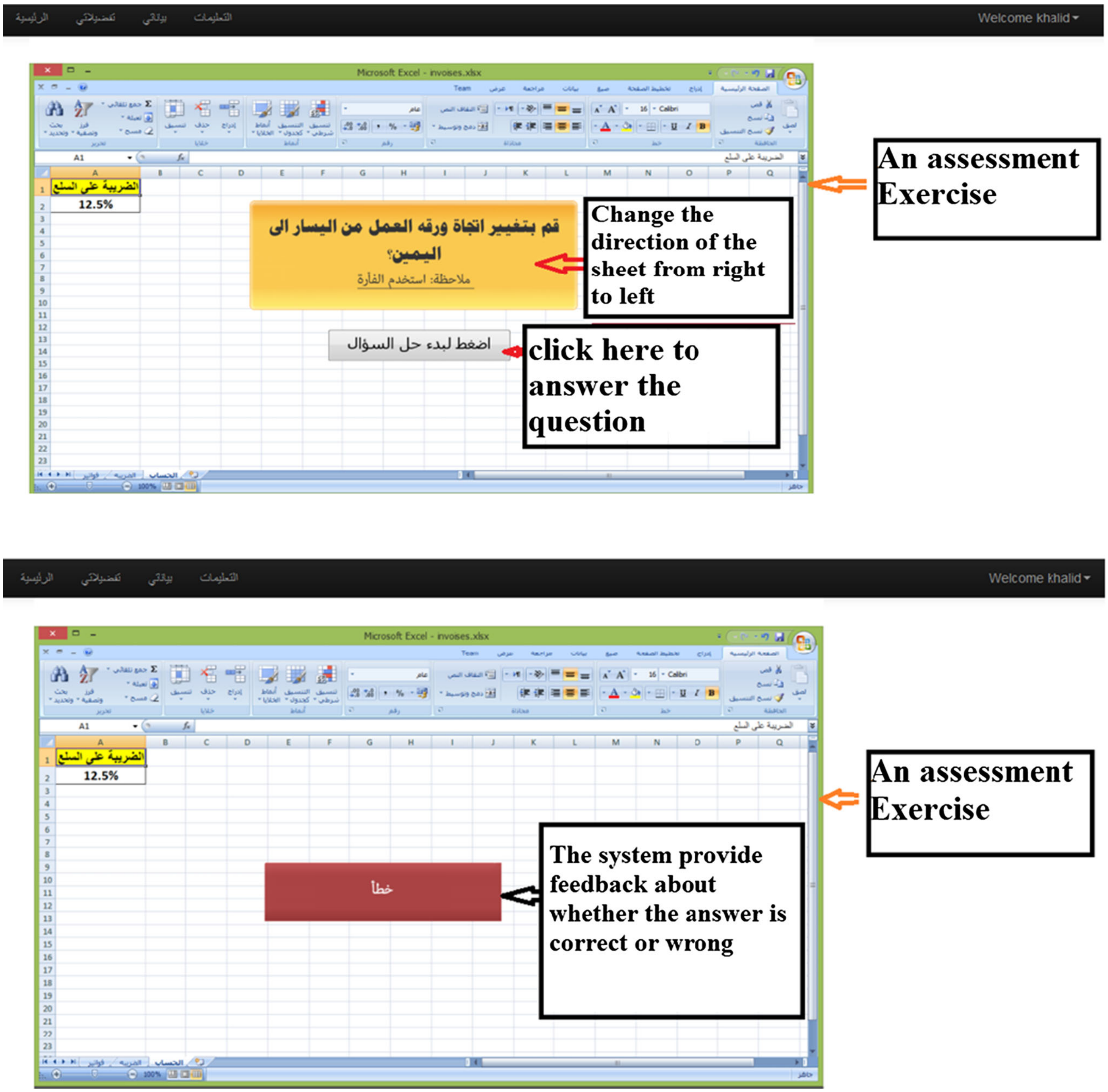

Fig. 12 Assessment exercise interfaces (with system feedback about whether the answer is correct)

2012; Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013):

$$\mu^{zcg}_{\tilde{B}^{h*}_c}\left(av^{(l)}\right) \geq \mu^{zcg}_{\tilde{B}^{h}_c}\left(av^{(l)}\right) \quad \text{for all h } = 1, \ldots\ldots, V_o \tag{17}$$

$\tilde{B}^l$ is chosen due to the B^{h*}, where $\mu^{zcg}_{\tilde{B}^h_c}(av^{(l)})$ is the z-weighted center of gravity of the membership of $\tilde{B}^h$ at $av^{(l)}$ as illustrated also in Eq. (11):

$$\mu^{zcg}_{\tilde{B}^h_c}\left(av^{(1)}\right) = \frac{1}{2}\left[\frac{\sum_l^I \bar{\mu}_{\widetilde{Z_l B^h_c}}\left(av^{(1)}\right) * z_l}{\sum_l^I z_l} + \frac{\sum_l^I \underline{\mu}_{\widetilde{Z_l B^h_c}}\left(av^{(1)}\right) * z_l}{\sum_l^I z_l}\right] \tag{18}$$

The proposed system can effectively handle the input/output data pairs, including multiple outputs as per the work presented above. Phase 1 is recognized as being distinct with regard to the number of outputs associated with each rule. In

Table 1 System inputs and their description

Input name	Description
Student gender	Students' gender whether male or female
Student age	Students' age whether teen, young, or middle-aged
Secondary school grade	The overall student grade in their secondary school: excellent, very good, pass, or fail
Student status	Whether they were full- or part-time students
Student course/ section of study in secondary school	Literacy section or scientific secondary section
Student level of knowledge in Excel	Current student level of knowledge in Excel during their learning within the system
Student level of knowledge in PowerPoint	Current student level of knowledge in PowerPoint during their learning activities

Table 2 System outputs and their description

Output name	Description
Difficulty level needed for Excel	The required difficulty level of Excel lessons, categorized as very easy, easy, moderate, difficult, and very difficult
Time needed for studying Excel	The time needed for studying Excel, categorized as very short, short, moderate, long, and very long
Difficulty level needed for PowerPoint	The required difficulty level of PowerPoint lessons, categorized as very easy, easy, moderate, difficult, and very difficult
Time needed for studying PowerPoint	The time needed for studying Power Points, categorized as very short, short, moderate, long, and very long

contrast, Phase 2 provides a straightforward expansion with the aim of enabling rules to encompass multiple outputs; for each output, the calculations detailed in Eqs. (15–17) are repeated.

5.3 The online adaptation and lifelong learning layer

5.3.1 The customization of knowledge delivery to students

The generated type-2 fuzzy sets and the fuzzy rules extracted from the input and output gathered learner data enable the proposed system to learn and obtain the best instructional actions in accordance with the current learners. The system is consequently able to readjust the online learning environment with specific consideration of the appropriate instructional actions. The system actions are triggered through the examination and monitoring of various learners' variables, which subsequently affect the online instructional environment, with particular consideration of the learned approximation of best instruction actions that will be generated for the learners. The followed architecture and functionality of the adaptive zSlices system, including type-reduction and defuzzification processes, are naturally inherited from the structure of a zSlices-based general type-2 FLS, as described in Wagner and Hagras (2010). At the end of these calculations, the crisp output reflecting the users' preference is presented to the users within the online learning environment.

5.3.2 Adaptive online life-long learning mechanism for dynamically updating selection and presentation of appropriate content

It is important for the proposed system to have the ability to be adjustable with respect to the dynamic and changing learners' needs and to constantly expand the students' knowledge levels by continuously enabling them to modify their instructional and learning needs. According to these modifications, the system will readjust its rules or apply new ones. In a given input state, if no rules fire from the rule base (i.e., the rule's firing strength in Eq. (13) $wi^{(t)} = 0$), the proposed system will actively record these inputs and the outputs (the instructional needs) to create a rule covering this uncovered input status. Thus, new rules would be added in the system when the state of the monitored online learning environment at that time is indeterminate per the existing rules in the rules base (i.e., when none of the present rules are fired). In such cases, the new rules will be extracted and the system will incorporate them, whereby the antecedent sets highlight the online environment's present input states with the consequent fuzzy sets reliant on the current state of instructional needs.

For all of the input parameters, the fuzzy sets that have membership values, where $\mu^{cg}_{\tilde{A}^h_c}(x_s^{(t')}) > 0$ are identified. As a result, for each input parameter, a number of identified fuzzy set(s) are generated in the form of a grid, from which new rules are generated based on all individual combinations of successive input fuzzy sets. The resulting fuzzy set that provides the greatest value of membership to the student defines the needed instructional variable (y_c) so that it can act as the extracted rule consequent. The resulting fuzzy sets can be established by conducting a calculation of the output memberships' center of gravity (Bilgin et al. 2012; Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013):

$$\mu^{zcg}_{\tilde{B}^{h*}_c}(y_c) \geq \mu^{zcg}_{\tilde{B}^{h}_c}(y_c) \tag{19}$$

For $h = 1, \ldots, W$ the $\tilde{B}_c$ is chosen as $\tilde{B}_c^{h^*}$, where $c = 1, \ldots, k$. Consequently, new and upcoming rules can be progressively added.

In case the user needs to change the suited instructional requirement at a given input status, the fired rules will be identified, and the rule consequents will be changed (if more than two students signal the same modifications for the instructional needed variables), as indicated in Eq. (19). Therefore, the fired rules are modified so that the updated suited instruction needs for the students could be reflected in a desirable way while considering the present state of the online learning environment.

This component enables the system proposed to adopt lifelong learning by facilitating the adaptation of rules according to the students' instructional needs, which notably change over time according to their capabilities and characteristics. Owing to the system's flexibility, the fuzzy logic model learned initially may be effortlessly expanded to make changes to both new and existing rules. These fuzzy rules enable a large range of values for all parameters (input and output) to be captured, which in turn enables the continuation of the generation of rules, even when the online learning environment gradually changes. Meanwhile, if notable changes occur in terms of the students' knowledge level (which may not be captured by the present rules, as highlighted above), the new rules will be automatically generated, which ultimately satisfies present conditions. Also, rules that are not activated and fired for a period of time (four weeks was found empirically to be a good number, but this might vary with other applications) will be automatically removed from the rule base to enable the efficient management of the rule base. This will enable the inconspicuous system to expand its actions and improve the instruction delivery by adhering to the students' needs.

Table 3 Sample from the collected dataset

Age	Gender	Secondary school grade	Student status	Section of study in secondary school	Level of knowledge in Excel	Level of knowledge in PowerPoint	Difficulty needed for Excel	Time needed for studying Excel	Difficulty level needed for PowerPoint	Time needed for PowerPoint
Teen	Male	Excellent	Full-time	Literacy	43.87	71.24	50	30	90	70
Young	Female	Good	Full-time	Scientific	84.2	62.39	95	55	55	20
Middle-aged	Male	Very good	Part-time	Literacy	53.44	45.51	50	50	30	50
Young	Male	Good	Full-time	Scientific	12.88	22.75	5	80	0	90

6 Experiments and results

We performed various real-world experiments at King Abdulaziz University in Saudi Arabia using a large-scale e-learning platform comprising 1871 students. We conducted these experiments using the fully developed e-learning platform to deliver PowerPoint and Microsoft Excel modules as the University permitted. The e-learning platform facilitated the examination of all adaptive proposed systems, which included a total of twenty-one learning units: twelve for Excel and nine for PowerPoint. Each unit combined various numbers of lessons, all of which offered training in different aspects of the Microsoft programs. Figures 4 and 5 demonstrate a full explanation of each of these learning units based on the approved course structure and contents from King Abdulaziz University.

As Fig. 6 illustrates, each lesson comprised five key components: PowerPoint slides explaining the lesson, a practical demonstration of the lesson, practical exercises, a video lecture explaining the lesson, and a final assessment task. An overview of these features using screenshots will be shown later.

1. The student views a text-based explanation of the module on PowerPoint slides. For instance, Fig. 7 shows how this lesson teaches students how to create line charts and pie charts.
2. A demonstration shows learners how to apply their new knowledge in practice, as Fig. 8 illustrates. For example, the lesson on creating a pie chart first directs students to select a range of cells and instructs them to click on the insert tab in the Charts group to select Pie and choose the most appropriate pie chart (Fig. 8).
3. The module provides relevant practical exercises for the students to complete to reinforce their abilities. If a student submits an incorrect answer, the system offers a hint. For instance, for the lesson "Changing the Sheet Direction," students must determine how to switch the orientation of the page from left to right. To do so, they are required to select the Page Layout tab. If they click on a different tab, the system offers a hint to assist them in making the correct choice by using a red rectangle to guide them toward the correct tab (Fig. 9). Students can make three attempts for each step of the task. If the student successfully makes a correct move—for instance, if he or she clicks on the Sheet Right-to-Left button in the sheet options—the system offers positive feedback and congratulates the student for making the correct choice (Fig. 10).
4. Fig. 11 presents a video featuring a lecturer discussing the lesson on creating pie charts and line charts.
5. The final lesson component is an assessment exercise that provides feedback to students, enabling them to see whether their answer is correct. This assessment dif-

Fig. 13 One example of an extracted rule from the produced rules

IF **Student-Age** *is* **Teen** *AND* **Student-Gender** *is* **Female** *AND* **Secondary-Grade** *is* **Excellent** *AND* **Method-of-Providing-Higher-Education** *is* **Full-Time** *AND* **the Secondary-Section** *is* **Science** *AND* **Average-Knowledge-in-Excel** *is* **Very Low** *AND* **Average-Knowledge-in-PowerPoint is Low,** *then the* **Suited-Excel-Difficulty-Level** is **Easy** *AND* **Needed-Time-to-Study-Excel** *is* **Very Long** *AND*

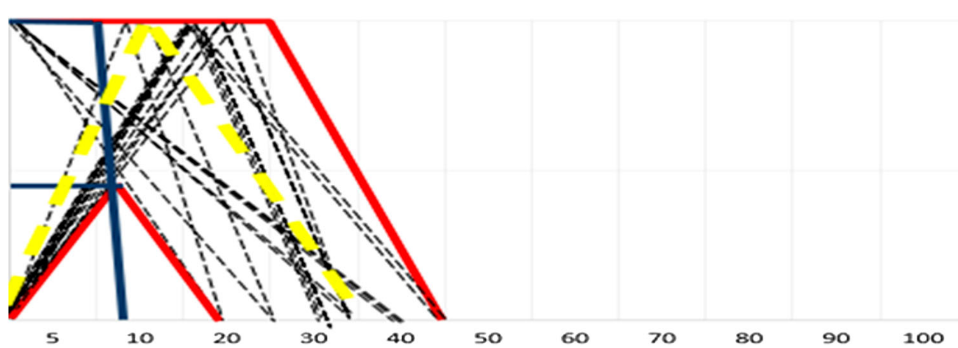

Fig. 14 An example of the extracted interval type-2 fuzzy set (very easy) and the type-1 fuzzy sets (*thick dashed yellow lines*) (color figure online)

fers from the earlier practical exercises, which offered only hints to guide the students. The user can make only one attempt at this exercise and receives feedback about whether the answer is correct (see Fig. 12).

The main aim of the experiment was to determine the relative performance of the zSlices-based general type-2 fuzzy system (zSlices-based GT2FS) compared to the interval type-2 fuzzy logic system (IT2FLS), the type-1-fuzzy-logic-based counterpart system (T1FLS), the instructor-led adaptation system, and the non-adaptive version, for the purposes of increasing instruction quality, bettering student performance, and enhancing overall students success rates. At the start of this study, a total of 1871 students were involved to participate with equal numbers of randomly chosen e-learners assigned to each group. The monitoring phase of the study required the students to register for the course and complete a cohesive pre-assessment to determine their existing knowledge of PowerPoint and Excel.

We collected the average scores for these two pre-assessment tests along with the students' gender, age, secondary school grade, status as full- or part-time status, and secondary school course of study to form the ***seven inputs for the fuzzy systems*** as described in Table 1. Subsequently, we deliberately revealed the average assessment results to the students so they could determine the appropriate content for their level and preference. **Four outputs** were collected from the students: the difficulty level they needed for Excel and PowerPoint, time needed for Excel, and time needed for PowerPoint as described in Table 2.

درجاتك ببرنامج الباوربوينت

الدرجة	عنوان الوحدة
14.29	فتح واستكشاف PowerPoint
25.0	التعامل مع العرض التقديمي
52.2	التعامل مع النصوص
77.0	التعامل مع الصور والكائنات
0.0	تحرير الشرائح
0.0	تنسيق الشرائح
0.0	أوامر العرض التقديمي والطباعة

Fig. 15 Pre-assessment results for a single student

درجاتك ببرنامج الباوربوينت

الدرجة	عنوان الوحدة
92.86	فتح واستكشاف PowerPoint
100.0	التعامل مع العرض التقديمي
88.24	التعامل مع النصوص
100.0	التعامل مع الصور والكائنات
40.0	تحرير الشرائح
100.0	تنسيق الشرائح
61.54	أوامر العرض التقديمي والطباعة

Fig. 16 Post-assessment results obtained from a single student

Once we collected the inputs and outputs for the proposed model (sample from the collected dataset is shown in Table 3), we constructed the zSlices-based GT2FS, IT2FLS, and T1FLS using the fuzzy sets to generate rules (see Fig. 13), as explained in Sect. 5.2.1. We used these fuzzy sets to analyze and manage the uncertainties associated with perceptions about modeling a particular linguistic label to determine learner characteristics and instructional needs. Figure 14 shows in solid red an example of the extracted interval type-2 fuzzy sets where the dashed yellow lines indicate the extracted type-1 fuzzy sets. A total of 30 students participated in constructing interval type-2 fuzzy sets; we required them to discuss their opinions on how such fuzzy sets should be modeled. On the other hand, two user groups contributed toward the construction of two interval type-2 fuzzy sets in the zSlice-based general T2FS; one group was drawn from the humanities section and the other from the scientific secondary section. The scientific section (high $z = 1$) was assigned more weight in the third dimension than the humanities section (high $z = 0.5$), as approximately 60 % of the users were drawn from the scientific section and were likely to study computer based courses in their secondary education.

The second phase of the experiment process provided adaptive course content on both Excel and PowerPoint to the third, fourth, and fifth user groups, who used a type-1-fuzzy-logic-based system (T1FLS), an applied interval type-2 fuzzy logic system (I2FLS), and an applied zSlice-based general type-2 fuzzy system (zSlices-based GT2FS), respectively. At the same time, the first group proceeded with the module using the non-adaptive system version, whereas the second group employed the instructor-led adaptation model that came with fixed rules devised based on expert knowledge. A more customizable module was given to students in the third, fourth, and fifth groups, who used an adaptive learning system that could be modified based on the user's unique learning needs. The rules in this case were generated based on different system users. A series of learning objects (LOs) were given to the users based on their chosen learning needs. In each lesson, all LOs were linked to two linguistic values correlated with the Excel and PowerPoint material's level of difficulty and the tendency for students to take longer learning PowerPoint and Excel topics. All 63 lessons across both modules were characterized by these features as the difficulty of the content fluctuated from very easy to more advanced, with different topics taking longer to complete. Following this stage in the experiment, we assessed the findings in order to evaluate the students' performance at the end of the semester. Figure 15 shows the results of a single student in the pre-assessment results, and their improvements after finishing the course is shown in Fig. 16.

We comparatively analyzed the results we obtained from the applied zSlice-based GT2FS environment, IT2FLS environment, T1FLS environment, fixed rule system (instructor-led adaptation model), and non-adaptive version. Figure 17 illustrates the extent to which students improved their performance based on their assessment scores before and after using the e-learning system. Based on the figures we present, the average scores of students using the zSlices-based GT2FS rose markedly by 26.45 %, indicating that this system yielded the most positive performance. We found that student scores increased by 26.04 % using IT2FLS, and 23.78 % using the T1FLS system, whereas the instructor-led adaptive system generated an increase of 20.48 %, and the non-adaptive version generated an increase of 19.06 % among the control group.

In addition, we analyzed the groups' mean of learning improvements from the pre-tests to the post-tests using ANOVA for comparison at a significance level of 0.05. The analysis revealed a significant statistical difference between the various groups ($p < .05$). We also carried out Tukey HSD and LSD comparison tests to see which pair of groups had the greatest difference. We observed that Group 5 (zSlices T2FLS with $M = 26.4512$ and $SD = 26.25757$) and Group 1 (controlled group with $M = 19.0681$ and $SD = 23.51329$) were the most significantly different groups as compared to other pairings, as shown in Fig. 18. Moreover, Group 5 (zSlices T2FLS) was significantly different from Group 2, which was the instructor-led adaptation model (with $M = 20.4895$ and $SD = 26.14493$), and a notable difference existed between the zSlices T2FLS and T1FLS groups (with $M = 23.7866$ and $SD = 25.37530$). The least significantly different groups, according to the results, were zSlices T2FLS and IT2FLS (with $M = 26.0491$ and $SD = 26.58322$).

Furthermore, we analyzed the rate of completion for all five groups, as Fig. 19 shows, finding that the total number of students who completed at least 90 % of the lessons with the zSlices-based general type-2 adaptive educational system exceeded the students in the other groups: 6.61 % improvement over those in the interval type-2 adaptive educational group, 8.23 % over those in T1FLS, 16.09 % over the instructor-led adaptive system group, and 17.26 % over the non-adaptive-based system's group. The improvement in the students' learning performance and completion rates indi-

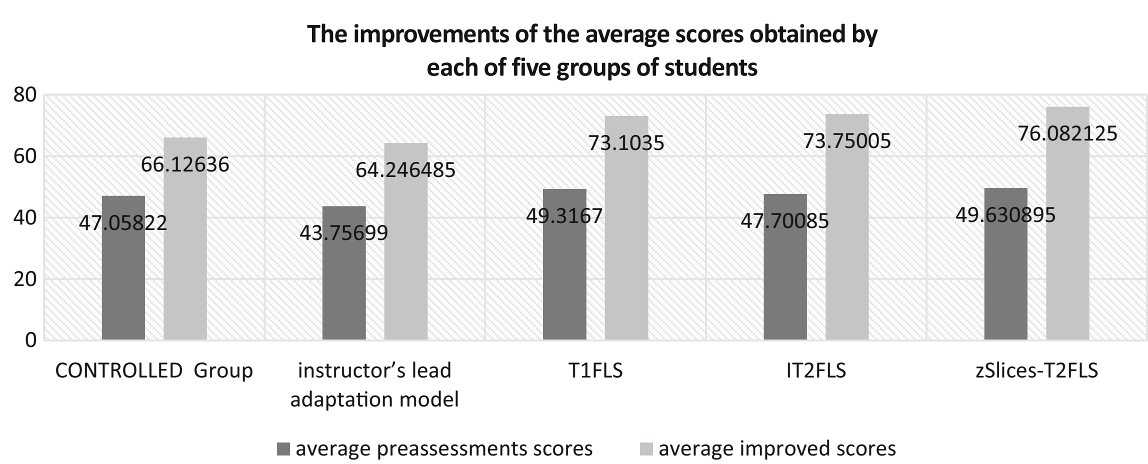

Fig. 17 Improvement in the average scores obtained from each of the five study groups before and after each system's application

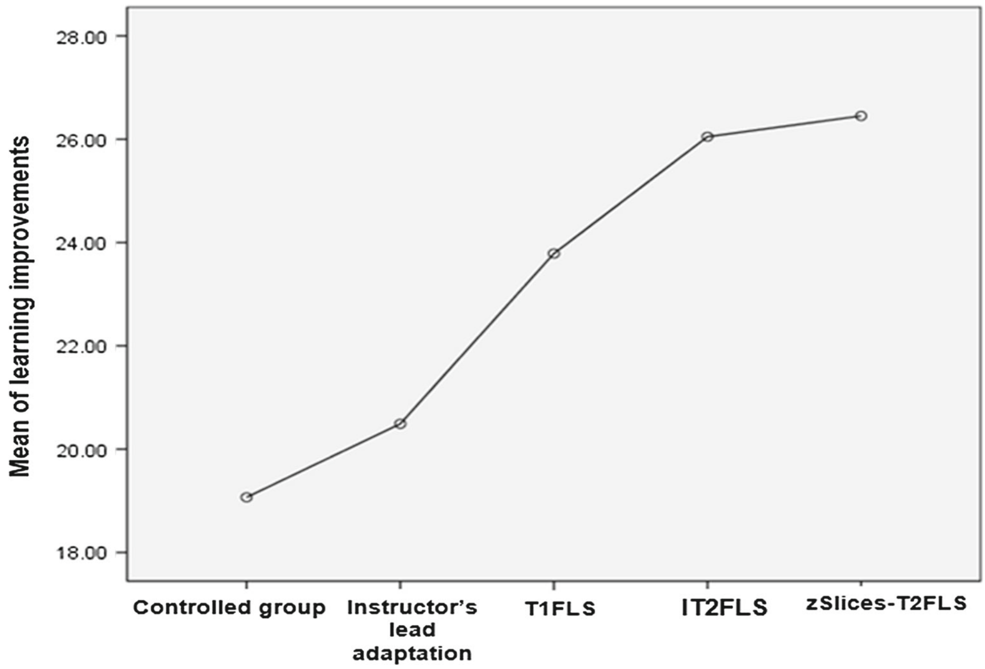

Fig. 18 Means plots for the groups' learning improvement

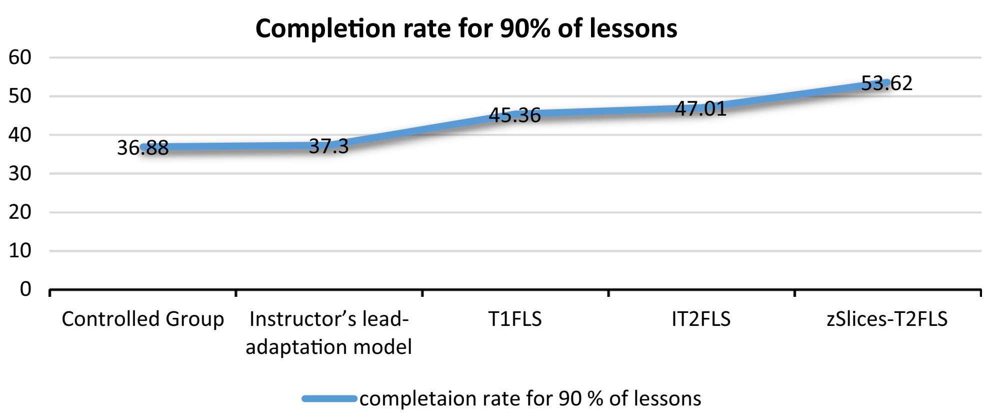

Fig. 19 Completion rate obtained by each of the five groups of students in the two study subjects after each system's application

Table 4 Average error (AE) and standard deviation (SD) of the system outputs

Output	T1FLS		T2FLS		zSlices-T2FLS	
	AE	SD	AE	SD	AE	SD
Level of difficulty needed for studying Excel	30.104	23.424	28.589	20.291	27.585	20.237
Needed time for studying Excel	32.130	26.131	28.758	21.831	28.14	21.64
Level of difficulty needed for studying PowerPoint	29.638	23.372	28.761	20.724	28.00	20.61
Needed time for studying PowerPoint	31.520	25.740	29.358	22.732	29.02	23.18

cates the effectiveness of the proposed zSlices-based GT2FS adaptive educational system compared with the other methods.

Table 4 presents the average error and standard deviation of the system outputs compared to the desired learner outputs. The collective dataset contained a total of 960 instances, 672 of which were classified as training data and 288 of which were classified as testing data. These results demonstrate that the zSlices-based GT2FS produces a lower average error rate and standard error deviation than the IT2FLS and T1FLS systems when comparing the system outputs with the student-desired outputs. This means that the zSlice-based GT2FS captures student behavior more effectively.

7 Conclusions and future work

In this paper, we have proposed a novel zSlices-based general type-2 fuzzy logic system that can determine different users' pedagogical needs and preferences in a dynamic online environment based on both their knowledge level and characteristics. This system's purpose is to improve student performance and increase completion rates of lessons by presenting students with tailored, adaptive content that matches their needs. This paper tested the zSlice-based GT2FS in comparison with the IT2FLS, the T1FLS, the instructor-led adaptive system, and the non-adaptive system. A large-scale e-learning platform in which 1871 King Abdulaziz University students participated facilitated the testing process.

The findings indicate that the zSlice-based GT2FS is more effective at managing uncertainty, lowering average errors and standard deviation, and increasing the overall completion rate by 6.61, 8.23, 16.09, and 17.26 % compared with the IT2FLS, T1FLS, instructor-led adaptation, and control groups, respectively. Furthermore, the zSlice-based GT2FS system achieved an improvement in student performance that was higher than that of the IT2FLS by 0.40 %, and higher than that of the T1FLS, instructor-led adaptation, and control groups by 2.66, 5.96, and 7.38 %, respectively.

These results clearly demonstrate that the proposed zSlice-based GT2FS can more effectively provide adaptive content to students. In the future, to incorporate a far greater range of inputs and outputs, we intend to implement the proposed model in a wider range of e-learning modules with thousands of registered students.

Compliance with ethical standards

Conflict of interest All the authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual human participants included in the study.

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