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An Interval Type-2 Fuzzy Logic Based System with User Engagement Feedback for Customized Knowledge Delivery within Intelligent E-Learning Platforms

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Abstract—Recent years have witnessed an expansion on realizing adaptive educational systems for intelligent E-learning platforms. Such platforms permit the development of customised learning contexts adapted to the requirements of every student by correlating the student characteristics with instructional variables. However, the vast majority of the existing adaptive educational systems do not learn from the users' behaviors to create white box models which could handle the linguistic uncertainties and could be easily read and analyzed by the lay user. Moreover, most of the existing systems ignore gauging the students' engagements levels and mapping them to suitable delivery needs which match the students' knowledge and preferred learning styles. This paper presents a novel interval type-2 fuzzy logic based system that can learn the users' preferred knowledge delivery needs and the preferred learning style based on the students' characteristics and engagement levels to generate a customized learning environment. The paper presents a novel system for gauging the students' engagement levels based on utilizing visual information to automatically calculate the engagement degree of students. This differs from traditional methods which usually employ expensive and invasive sensors. Our approach only uses a low-cost RGB-D video camera (Kinect, Microsoft) operating in a non-intrusive mode whereby the users are allowed to act and move without restrictions. The efficiency of the proposed system has been tested through various real-world experiments with the participation of 15 students. These experiments indicate the ability of the proposed type-2 fuzzy logic based system to handle the linguistic uncertainties to produce better performance in terms of improved learning and better user engagements when compared to type-1 based fuzzy systems and non-adaptive systems.

I. INTRODUCTION

In a normal classroom, when the student has low satisfaction, engagement and lower educational performance, the teachers might not know the main causes of this so that they can act to strengthen student performance and grab their attention and engagement during the learning activities. This problem arises due to different student engagement levels and characteristics based on the teaching style,the taught content of the teacher and the learning activities. Hence, there are limits to the degree to which any teacher can tailor the learning environment to ideally educate every student synchronically due class size and the precision of the carried evaluation process of the teacher. Thus, the accuracy of analyzing the students' characteristics can be facilitated by a smaller student number, which would allow teachers to concentrate on the requirements and preferences of each individual student [1]. It has been revealed that there are opportunities for better student learning outcomes, motivation and levels of engagement through one-on-one teaching [2]. However, the provision of such focus and teaching in traditional classes could be difficult.

E-learning courses are becoming increasingly more popular where more than 30 million online students are registered for higher education taking one or more classes online [3]. More than 50% of these students are in USA where at least one class was taken online by around 16.1 million students in 2011, whereas all classes were taken online by 1.5 million students [3]. It is projected that by 2016 in USA, this number will rise to around 4.1million students [3]. These numbers emphasize the importance of e-learning in the World, and the way e-learning is turning into a main mode of provision of higher education [4]. However, many problems remain with e-learning environments. Several of these problems are similar to ones that arise in conventional classes, pertaining to the dearth of interpersonal interaction. Furthermore, there are generic courses provided online which are not personalized to the individual needs of the students. These difficulties can lead to the hindrance of the students' performance and engagement levels. In order to provide better e-learning platforms, there is a need to have a good understanding of individual students' needs in terms of their knowledge levels, preferred styles of learning and engagement levels, so that the platform can provide a customized teaching style. Consequently, adaptive educational learning environments are utilized [1]. Since individualized learning systems enhance students' learning performance through provision of instructional material as per the particular personalized needs and preferences of every student, there has been increased interest in various adaptive learning systems [5, 6].

A number of factors impact the learning requirements and preferences of students related to learning style, motivation, knowledge level, goals, and attention state [5]. Based on the evaluation of these characteristics, the instructional process can be personalized to improve the content presentation and information of materials to suit the requirements of every student, thus aiding students to accomplish higher learning outcomes and engage with the learning environment [7]. Thus, automatic and continuous learning within the preferred learning style and preferred knowledge delivery needs for students are important factors to optimize student learning outcomes, engagement and satisfaction. In order for students to obtain knowledge from the course they need to engage with it, regardless of how the course is delivered [8]. The more a student engages with the content of the course, the more information they will absorb [8], hence if a course can be better tailored to the student they will inevitably learn more [8]. Hence, our research seeks to correlate and learn the preferred learning style and knowledge's delivery needs of students based on their characteristics and their levels of engagement.

The efficiency of adaptive educational systems relies upon the methodology used to gather information pertaining to the learning needs of students and also on the way this information is processed to form a customized learning context [6]. However, the question arises of how one can ensure precision in evaluating individuals' knowledge delivery needs, preferred styles of learning and other requirements of personalized knowledge delivery. This question is quite critical, due to several uncertainties in how accurately students' responses are actually assessed by adaptive educational methods, as well as the corresponding uncertainties associated with how the resulting instruction to the student is actually understood and received. In e-learning environments, there are 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 the their levels of engagement, knowledge and future plans [9]. In order to tackle the uncertainty that may inhibit the advancement of an efficient learning context, it is suggested that any adaptive educational system should incorporate flexible Artificial Intelligence (AI) methods [9].

A number of AI-based approaches have been adopted in order to achieve adaptive educational systems. These techniques include fuzzy logic, neural network, Bayesian networks and hidden Markov Models. While several adaptive educational systems employ AI methodologies, they do this in varying ways. For example, some of the systems are based on the evaluation and examination of students' characteristics [10, 11, 12, 16], while others are employed in facilitating diagnostic process completion [10, 13, 14, 15].This allows for the adjustment of the contents of the course in order to fit the students' requirements. Nevertheless, when considering some of those approaches (namely Bayesian networks, Hidden Markov Models and neural network) there is a problem in terms of knowledge representation, meaning that such AI approaches are not able to establish transparent human behaviour frameworks [16]. One further restriction of such approaches is that they require the repetition of time- consuming iterative learning methods so as to fulfil framework amendments following the continuously changing and dynamic nature of the e-learning process [10]. In addition, the majority of employed AI approaches do not learn from user behaviours to create easily read and understood white box models that could handle high levels of uncertainties. Fuzzy logic systems are well known for their ability to generate white box models that can handle high levels of uncertainties. However the vast majority of fuzzy logic systems employ type-1 fuzzy logic systems which handle the encountered uncertainties based on precise type-1 fuzzy sets[17].In contrast, interval type-2 fuzzy logic systems can handle the uncertainties encountered through interval type-2 fuzzy sets which are characterized by a footprint of uncertainty (FOU) which provides an extra degree of freedom to enable handling high uncertainty levels [17].

This paper presents an interval type-2 fuzzy logic based system that can learn the users' preferred knowledge delivery needs and the preferred learning style based on the students' characteristics and average engagement degree during the learning activities to generate a customized learning environment. The type-2 fuzzy model is first created from data collected from a number of students with differing capabilities and needs. The learnt type-2 fuzzy-based model is then used to improve the knowledge delivery to the various students based on their individual characteristics and engagement levels. We will show how the presented system enables customizing the learning environments to improve individualized knowledge delivery to students which can result in enhancing the students' performance and increase their engagement and motivation. The proposed system is able to continuously respond and adapt to students' needs on a highly individualized basis. Thus, online courses can be structured to deliver customized education to the student based upon various criteria of individual needs and characteristics. The efficiency of the proposed system has been tested through various experiments with the participation of 15 students. These experiments indicate the ability of the proposed type-2 fuzzy logic based system to handle the linguistic uncertainties to produce performance (in terms of learning outcomes and engagement) superior to that of type-1 based fuzzy systems and non-adaptive systems.

Section II presents a brief overview on the need to consider students' engagement degrees in adaptive educational systems. Section III presents a brief overview on interval type-2 fuzzy logic systems. Section IV presents a brief overview on the application of fuzzy logic systems in education and e-learning. Section V presents the proposed type-2 fuzzy logic based system for knowledge delivery personalization within intelligent e-learning platforms. Section VI presents the experiments and results, and the conclusions are presented in Section VII.

II. The Need to Consider Students' Engagement Degrees in Adaptive Educational Systems

In studying student needs in various teaching settings, there is a need to understand student variables and the manner in which students intend to enhance such variables accordingly. A detailed review about personalization variables for the learner that require modifications within the learning setting and the principle strategies known as pedagogic personalization employed in managing such variables can be found in [5, 6].

A major pitfall in the modern implementation of e-learning is that the learner models disregard student engagement and do not map delivery needs in terms of knowledge level and preferred learning style. Estimating the engagement degree of users robustly and automatically is a key procedure for various applications and research topics and has been widely studied in different laboratories and semi-constrained environments. A typical non-contact approach to measure engagement is eye gaze behaviour recognition, whereby eye behaviour is analysed using eye tracking devices. A study of responses to advertisements found that the number of eye fixations is a robust feature demonstrating the strength of attention and engagement [18].However, eye tracking devices are expensive sensors and they are not convenient to be used in real-world unconstrained environments. Therefore, higher-level systems using multiple hybrid sensors were studied. In [19], hybrid sensors including Kinect camera, skin sensor, and webcam were utilized to analyse the engagement degree of employees in office environments. In [20], a pressure sensor and an IR camera were used to estimate the interest and engagement extent of the students. However, the system complexity and costs are greatly increased, which limits the scalability of the system, even though combining hybrid sensors increases the analysis accuracy.

From the above discussions, it is obvious that incorporating learner engagements as a learner personalization variable enriches the learning environments with a highly crucial pedagogical dimension. This work presents a cheap and non-intrusive means for measuring the student engagement.

III. A Brief Overview on Type-2 Fuzzy Logic Systems

The interval type-2 Fuzzy Logic System (FLS) depicted in Fig. 1a uses interval type-2 fuzzy sets (such as the type-2 fuzzy set shown in Fig. 1b) to represent the inputs and/or outputs of the FLS. In the interval type-2 fuzzy sets all the third dimension values are equal to one. The use of interval type-2 FLS helps to simplify the computation (as opposed to the general type-2 FLS) [17].

The interval type-2 FLS works as follows: the crisp inputs are first fuzzified into input type-2 fuzzy sets; singleton fuzzification is usually used in interval type-2 FLS applications due to its simplicity and suitability for embedded processors and real time applications. The input type-2 fuzzy sets then activate the inference engine and the rule base to produce output type-2 fuzzy sets. The type-2 FLS rule base remains the same as for the type-1 FLS but its Membership Functions (MFs) are represented by interval type-2 fuzzy sets instead of type-1 fuzzy sets. The inference engine combines the fired rules and gives a mapping from input type-2 fuzzy sets to output type-2 fuzzy sets. The type-2 fuzzy output sets of the inference engine are then processed by the type-reducer which combines the output sets and performs a centroid calculation which leads to type-1 fuzzy sets called the type-reduced sets. There are different types of type-reduction methods. In this paper we will be using the Centre of Sets type-reduction as it has a reasonable computational complexity that lays between the computationally expensive centroid type-reduction and the simple height and modified height type-reductions which have problems when only one rule fires [17]. After the type-reduction process, the type-reduced sets are defuzzified (by taking the average of the type-reduced sets) to obtain crisp outputs. More information about the interval type-2 FLS can be found in [17].

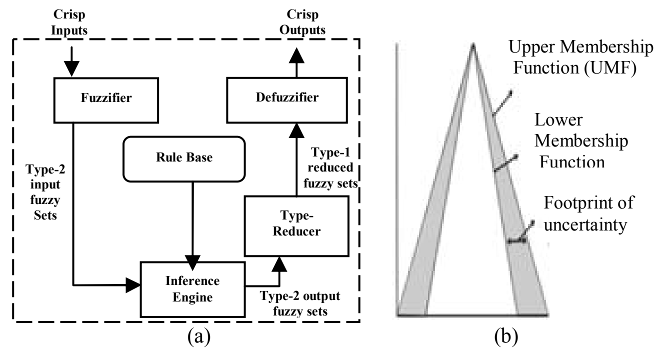

Fig. 1. (a) Structure of the type-2 FLS [17] (b) An interval type-2 fuzzy set.

In Fig. 1b, the shaded area is labeled as Footprint of Uncertainty (FOU) which is bounded by lower membership function $\underline{\mu}_{\tilde{A}}(x)$ and an upper membership function $\overline{\mu}_{\tilde{A}}(x)$[17].

Thus an interval type-2 fuzzy set is written as follows:

$$\tilde{A} = \int_{x\in X}\left[\int_{u\in\left[\underline{\mu}_{\tilde{A}}(x),\overline{\mu}_{\tilde{A}}(x)\right]} 1 / u \ \right]/x \qquad (1)$$

IV. A Brief Overview on the Application of Fuzzy Logic Systems in Education and E-Learning

A FLS can be used to summarize students' preferences in terms of knowledge acquisition and understanding [9]. A framework based on FLS and tailored to user-modelling induces easy reasoning for designers and users thus facilitating both comprehension and amendments [21], [22]. Additionally, FLSs are widely employed in examining and assessing the results related to knowledge and learning [11], [12],[23]. Therefore, FLSs can be used in examining and evaluating multiple criteria assessment and task objectives as shown earlier studies [11],[12],[23].Nevertheless, it is unusual for FLSs to be adopted for adaptive presentation of course contents in educational system. According to [13], the employment of profiling system adopting multi-agent methodology has been presented where fuzzy models were employed for students and content was grounded on a dynamic plan which was earlier defined for a single individual. The framework was achieved via profile construct which is known to comprise of learning tasks tailored for students. This framework considers the current topics and the time taken on the topics. In addition, the content framework was made to contain fuzzy connections between the users' knowledge and the subjects. This concept, known as pre-requisite relations, was created to officially define the learning strategy in terms of the sequence of issues that need to be studied by the user [13]. However, in this study, students' behaviours are predicted using criterion connections between the knowledge of students and topics and their behaviours. This is further achieved by creating a dynamic studying strategy for the student. Contrary to the situation with the system presented in this paper, students' requirements [13] were not automatically learned via the large data set which was collected from different students. Within the research regarding this system, a number of limitations arose. Despite the sizeable sample data collated from students, results of student requirements were not readily apparent. There was also little evidence of the adaptations required within the framework that would guarantee that the system reflects the dynamic nature of student preferences. It was expected that framework adjust to the ever evolving students' preferences. 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.

V. The Proposed Type-2 Fuzzy Logic Based System for Improved Knowledge Delivery Within Intelligent E-Learning Platforms

The proposed system seeks to tailor the knowledge delivery within intelligent e-learning platforms according to students' individual knowledge needs in terms of their knowledge levels and preferred learning styles. Fig.2 shows an overview of the proposed system, whereby the data is gathered through assessing students' knowledge delivery needs, as held by students, according to their characteristics variables and engagement level in the online learning environment. The data is then used for the generation of the MFs and rules associated with interval type-2 fuzzy logic system. The employed type-2 fuzzy sets generation approach is based on [24], which is a method centred on creating type-2 fuzzy sets via the gathering of type-1 fuzzy sets information from participants. The type-1 fuzzy sets derived are combined, thus resulting in the FOU, which accordingly induces a type-2 fuzzy set, which is seen to signify a word. Furthermore, an unsupervised one-pass approach, as motivated through [17, 25, 26], is utilized by our system with the aim of extracting the rules from the data collected which will help to describe the knowledge delivery needs of students, and will be used to build a model that learns their behaviours. The students' learned behaviours will be taken into account and will subsequently create an output in consideration to the current state of inputs. Accordingly, this type-2 FLS will make changes to the online learning environment in relation to the learned behaviours of the students, and will further enable the online adaption and enhancement of rules. This facilitates long-term learning owing to the changing of the performance, engagement levels and delivery preferences of the students.

The proposed system comprises five phases (as shown in Fig.2) which will be discussed in detail in the following subsections.

1) Capturing the Input and Output Data

Initially, our system gathers and captures the students' data through assessing the students' knowledge delivery requirements with the preferred learning style, alongside their characteristics and the engagements levels within the online learning environment. Importantly, upon the change in an individual student knowledge delivery need, characteristic or engagement levels, the system will actively record the data (both current inputs and outputs). Thus, our system creates and learns a descriptive model of the students' knowledge delivery needs and characteristics; this is achieved through the data gathered, generating a set of multi-input and output data pairs, which take the following form [17],[25],[26]:

$$x^{(t)}; y^{(t)} \qquad (t = 1,2,\dots,N), \tag{2}$$

Where N is recognized as the number of data instances, $x^{(t)} \in R^n$,and $y^{(t)} \in R^k$. Our system extracts rules which explain how the k output knowledge delivery variables $y = (y_1, \ . \ . \ . , y_k)^T$ are impacted by the input variables $x = (x_1, . \ . \ . , x_n)^T$. A model mapping inputs to outputs is achieved by the established fuzzy rules, without requiring a mathematical model. Therefore, individual rules can be adapted online, affecting only certain aspects of the descriptive model created and learned by the proposed system.

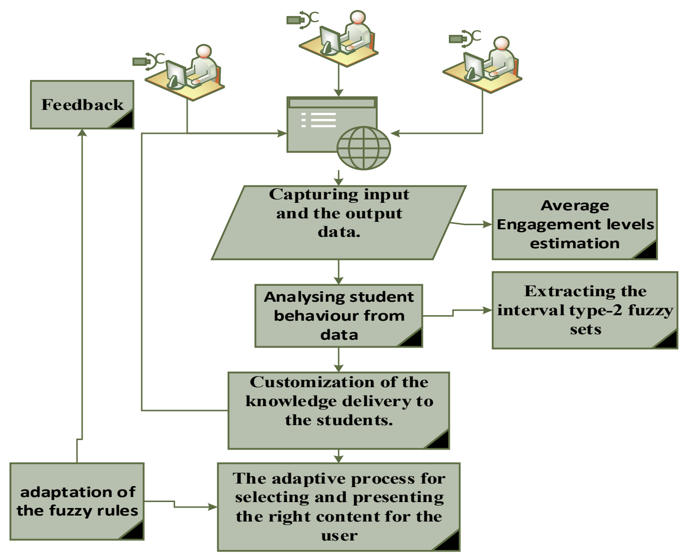

Fig. 2. An overview on the proposed type-2 fuzzy logic based systems for improved knowledge delivery within intelligent e-learning platforms.

1.1) The proposed method for capturing the Engagement Degree

Firstly, the head pose is computed from Kinect camera using the Kinect for Windows SDK (as shown in Fig. 3a). After that, the deviation degrees of the current head orientation away from the monitor are calculated to measure the extent of distraction. Finally, we select the largest distraction extent degree to estimate the engagement degree of the student. More details are discussed below.

1.1.1) Head Pose Estimation

Recently head pose estimation has received a major attention as an important procedure for human behaviour recognition. With depth cameras such as Microsoft Kinect, Panasonic D-Imager and PrimeSense 3D Sensors becoming available at competitive prices, the research focus of head pose estimation has shifted from 2D video analysis to 3D (RGB-Depth) information analysis, which obtains better accuracy and performance compared to 2D methods [27, 28, 29]. The Microsoft Kinect supports the capture of 2D RGB video stream and 3D depth stream at real-time speed (30 frames per second) utilizing advanced techniques of infrared projection and light coding. However, the depth information captured from Kinect is not as accurate or robust as data acquired by other expensive devices, such as laser sensors. To address this problem and improve the accuracy of the estimation results, the method reported in [30] was employed. The algorithm is based on a regularized maximum likelihood Deformable Model Fitting (DMF) approach to reduce impact of noise factors in the depth channel. Since this approach has been done in the latest version of Kinect Windows SDK, we utilize the module directly to perform head pose estimation on the student (user) in e-learning environments, as shown in Fig. 4. The Kinect SDK provides and describes head pose relating to the Kinect camera by three angles: pitch, roll and yaw, as demonstrated in Fig. 3 b. The three angles are illustrated in degrees ranging from -90 to +90 degrees.

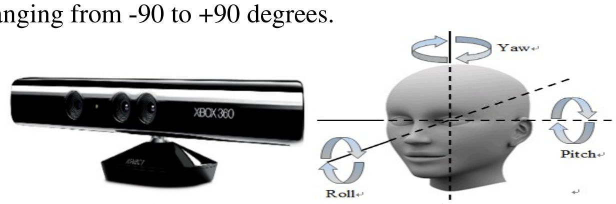

Fig. 3. (a) The used Kinect camera (b) Head pose angles (Yaw, Pitch and Roll)

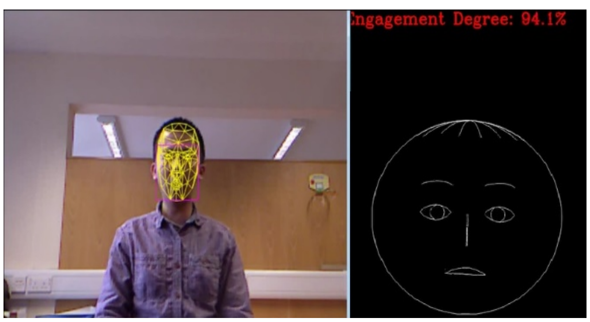

Fig. 4. Head pose estimation

1.1.2) Engagement Degree Estimation

Since the head pose can perform a continuous state on all the three degrees of freedom based on which engagement estimation is performed, we will consider the following assumptions describing the relation between the head pose angles and engagement degree:

- Facing front/towards the monitor – the student (user) is engaged in the online learning.
- Facing down – the student is sleepy or probably playing a tablet/Smartphone.
- Facing to the left/right –the user is distracted from the learning and interacting with another student nearby.
- Looking around –The student is thinking about irrelevant problems and is not concentrated.

Based on the assumptions above, the engagement degree of the student can be calculated and modeled by the deviation between the current head orientation and the optimum engaged head pose (facing towards the screen/monitor) which is shown in the following equations.

$$Engagmentdegree = 1 - Max(Deviation_p, Deviation_r, Deviation_p\} \quad (3)$$

$$Deviation_p = 1 - \frac{|Pitch_c - Pitch_o|}{Pitch_{max}} \quad (4)$$

$$Deviation_r = 1 - \frac{|Roll_c - Roll_o|}{Roll_{max}} \quad (5)$$

$$Deviation_y = 1 - \frac{|Yaw_c - Yaw_o|}{Yaw_{max}} \quad (6)$$

Where Pitch_c,$\mathrm{Roll}_c \mathrm{Yaw}_c$ are the three angles (pitch, roll and yaw) of the current head pose obtained by the algorithm of Kinect head pose estimation.Pitch_o,Roll_o,Yaw_o are the angles describing the optimum engaged head pose which are recorded in the initialization stage of the system. Pitch_{max},Roll_{max}, Yaw_{max} are the maximum angles defined in the Kinect SDK.

2) Extracting the Interval Type-2 Fuzzy Sets

It is essential that the gathered students' input/output data be categorized via the relevant fuzzy membership functions. This provides quantification of the raw input and output values, changing them into linguistic labels, for instance very low/low and high/very high. The approach detailed in [24] is implemented, which creates a type-2 fuzzy set, the FOU of which embeds the numerous type-1 fuzzy sets seen to signify each student's individual view concerning a particular linguistic label explaining the characteristics, preferences and requirements. Accordingly, for the type-2 fuzzy sets, the generated FOU will combine the various perspectives of students relating to modelling such words and will handle the uncertainties. In the employed approach, the data are gathered through questioning the participants on their views relating to particular linguistic labels, which will generate type-1 fuzzy sets. Following this stage, utilising the approach of [24], the type-2 fuzzy sets are constructed where the type-1fuzzy sets (representing the student individual preferences) are combined, resulting in the FOU of the type-2 fuzzy set which represents the given word. Through the application of the Representation Theorem [17], [24], each of the interval type-2 fuzzy sets $\tilde{A}_s$can be calculated as follows:

$$\tilde{A}_s = \cup_{i=1}^{n} A^i \quad (7)$$

Where $A^i$is referred to as the i^{th}embedded type-1 fuzzy set and $\cup$ is an aggregation operation [24]. The process of generating $\tilde{A}$ *is* based on approximating the upper MF$\overline{\mu}_{\tilde{A}}(x)$ and the lower MF $\underline{\mu}_{\tilde{A}}(x)$of $\tilde{A}_s$. This will depend on shape of the embedded type-1 fuzzy sets and the FOU model which is to be generated for $\tilde{A}_s$. In our system we use interior FOU models, right and left shoulder MFs (shown in Fig. 5 a, 5 b and 5 c) for the upper and lower MF parameters from all the embedded non-symmetric triangle type-1 MFs. As shown in Fig. 5a, the resulting interior interval type-2 fuzzy set is described by parameters: $\underline{a}_{MF}$, $\underline{c}_{MF}$, $\overline{c}_{MF}$ and $\overline{b}_{MF}$ denoting a trapezoidal upper MF and the parameters: $\overline{a}_{MF}$ and $\underline{b}_{MF}$ for a non-symmetric triangular lower MF, with an intersection point (p, μ_p) [24].The procedures for calculating these parameters are now described as follows:

Given the parameters for the triangle type-1 MFs generated for each of the i students $[a^i_{MF}, b^i_{MF}]$, the procedure for approximating the FOU model for interior FOUs is as follows [24]:For the upper MF $\overline{\mu}_{\tilde{A}}(x)$, we need to follow the following steps:

(1) For $\mu(x) = 0$, , find $\underline{a}_{MF}$ to be equal to the minimum $a^{min}_{MF}$of all left-end points a^i_{MF} and $\overline{b}_{MF}$ to be equal to the maximum $b^{max}_{MF}$of all right-end points b^i_{MF}[24].

(2) For $\mu(x) = 1$, find $\underline{c}_{MF}, \overline{c}_{MF}$ which correspond to the minimum and the maximum of the centers of the type-1 MFs.

(3). Approximate the upper MF$\overline{\mu}_{\tilde{A}}(x)$by connecting the following points with straight lines: $(\underline{a}_{MF}, 0)$, $(\underline{c}_{MF}, 1)$, $(\overline{c}_{MF}, 1)$ and $(\overline{b}_{MF}, 0)$. The result is a trapezoidal upper MF as depicted in Fig. 5a.

The steps to approximate the lower MF $\underline{\mu}_{\tilde{A}}(x)$are as follows:

(1) For $\mu(x) = 0$, find $\overline{a}_{MF}$ to be equal to the maximum $a^{max}_{MF}$of all left-end points a^i_{MF} and $\overline{b}_{MF}$ to be equal to the minimum b^{min}_{MF} of all right-end points b^i_{MF} [24].

(2) Compute the intersection point (p, μ_p) by the following equations [24]:

$$p = \frac{\underline{b}_{MF}(\overline{c}_{MF} - \overline{a}_{MF}) + \overline{a}_{MF}(\underline{b}_{MF} - \underline{c}_{MF})}{(\overline{c}_{MF} - \overline{a}_{MF}) + (\underline{b}_{MF} - \underline{c}_{MF})} \quad (8)$$

$$\mu_p = \frac{(\underline{b}_{MF} - p)}{(\underline{b}_{MF} - \underline{c}_{MF})} \quad (9)$$

(3) Approximate the lower MF $\underline{\mu}_{\tilde{A}_s}(x)$A by connecting the following points with straight lines: ($\underline{a}_{MF}, 0)$, $(\overline{a}_{MF}, 0)$, $(p, \mu(\mathrm{p}))$, $\underline{b}_{MF}, 0)$ and $(\overline{b}_{MF}, 0)$.The result is a triangle lower MF as shown in Fig. 5a.The procedure we employ for computing the FOU for right and left shoulder is the same as described in [24].

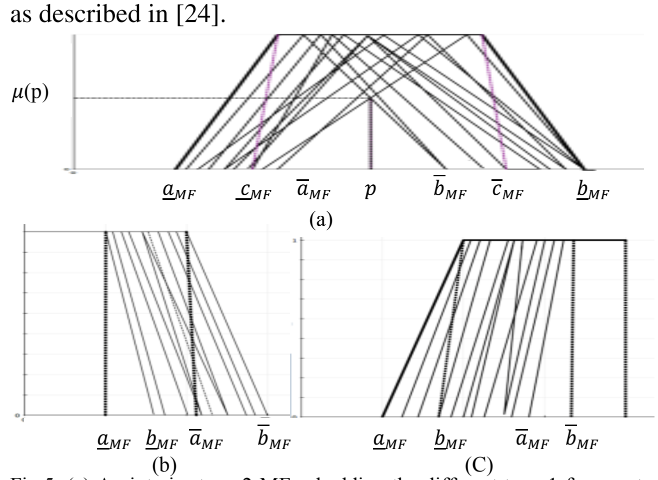

Fig.5. (a) An interior type-2 MFembedding the different type-1 fuzzy sets , (b) left shoulder type-2 MF embedding the different type-1 fuzzy sets (c) Right shoulder type-2 MF embedding the different type-1 fuzzy sets[24].

3) Extracting the Fuzzy Rule from the Collected Data

The generated interval type-2 fuzzy sets are mixed with the data of accumulated user input/output with the aim of extracting the rules explaining the behaviours of individuals. The rule extraction method employed in this paper is based on an improved form of the Wang-Mendel approach [17], [25], [26]. The type-2fuzzy system considered in this paper extracts various multiple-input–multiple-output rules, which are known to explain the relation between $x = (x_1, \ldots, x_n)^T$ and $y = (y_1, \ldots, y_k)^T$, and adopt the following form:

$$IF\ x_1 \text{ is } \tilde{A}^l_1 \ldots \text{and } x_n \text{ is } \tilde{A}^l_n \text{ THEN } y_1\ is\ \tilde{B}^l_1 and\ y_k\ is\ \tilde{B}^l_k \quad (10)$$

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

Notably, there are $V_i$interval type-2 fuzzy sets$\tilde{A}^q_s$, $q = 1, \ldots, V_i$ explained for each input x_s where $s = 1,2, \ldots, n$. There are V_o interval type-2 fuzzy sets $\tilde{B}^h_c$, $h = 1, \ldots, V_o$, explained for each output y_c where $c = 1,2, \ldots, k$, the V_i input interval type-2 fuzzy sets.

In an attempt to explain and abridge the subsequent representation, the approach for those rules comprising a single output is demonstrated owing to the fact that the method is relatively simple to expand in regard to rules involving numerous outputs. The various stages involved in this rule extraction are shown below.

Stage 1: In regard to a fixed input–output pair, $(x^{(t)}; y^{(t)})$ in the dataset $(t = 1,2, \ldots, N)$, the upper and lower membership values are computed $\overline{\mu}_{\tilde{A}^q_s}(x^{(t)}_s)$and $\underline{\mu}_{\tilde{A}^q_s}(x^{(t)}_s)$for each of the fuzzy set$\tilde{A}^q_s$, $q = 1, \ldots, V_i$, as well as for each input variable $s(s = 1, \ldots, n)$. Find $q^* \in \{1, \ldots, V_i\}$such that[17], [25], [26]:

$$\mu^{cg}_{\tilde{A}^{q^*}_s}(x^{(t)}_s) \geq \mu^{cg}_{\tilde{A}^q_s}(x^{(t)}_s) \quad (11)$$

For all q = 1,...,V_i .Notably, $\mu^{cg}_{\tilde{A}^q_s}(x^{(t)}_s)$ is the centre of gravity of the interval membership of $\tilde{A}^q_s$ at $x^{(t)}_s$ as can be seen below [17]:

$$\mu^{cg}_{\tilde{A}^q_s}(x^{(t)}_s) = \frac{1}{2}\left[\overline{\mu}_{\tilde{A}^q_s}(x^{(t)}_s) + \underline{\mu}_{\tilde{A}^q_s}(x^{(t)}_s)\right] \quad (12)$$

The following rule will be referred to as the rule generated by $(x^{(t)}; y^{(t)})$ [17], [25], [26]:

$$IF x_1 \text{is } \tilde{A}^{q^{*(t)}}_1 . \text{and} x_n \text{ is } \tilde{A}^{q^{*(t)}}_n \text{THEN } y \text{ is centered } at\ y^{(t)} (13)$$

For all of the input variables x_s there are $V_i$type-2 fuzzy sets $\tilde{A}^q_s$, which enables the greater amount of potential rules equal to V^n_i.Nevertheless, when considering the dataset, there will be the generation of those rules amongst the V^n_i possibilities that show a dominant region comprising a minimum of one data point.

In the first stage, there is the creation of one rule for each respective input–output data pair, with the fuzzy set selected being that which is seen to achieve the greater value of membership at the data point, and notably selected as the one in the rule's IF element. Nevertheless, this is not the finalised version of the rule, which will be calculated in the subsequent step. Notably, the computation of the rule weight is carried out as follows [17], [25], [26]:

$$wi^{(t)} = \prod_{s=1}^{n} \mu_{\tilde{A}_s^q}^{cg}\left(x_s^{(t)}\right) \quad (14)$$

A rule $wi^{(t)}$ weight is a measure of the strength of the points $x^{(t)}$ belonging to the fuzzy region the entire rule encompasses.

Stage 2: There is the repetition of the first stage for all of the data points from 1 to *N*; this helps to obtain *N* data generated rules in the form of Equation (13). Owing to the fact that there are a significant number of data points comprising numerous similar instances, Stage 1 witnesses the creation of multiple rules, all of which have the same IF part in common but which are all conflicting. During this stage, those rules seen to have the same IF part are amalgamated to form a single rule. Accordingly, the rules *N* are divided into groups, with rules in each of the groups seen to have the same IF part. If it is considered that such groups amount to M, it may also be stated that the group has N_l rules, thus [17], [25], [26]:

$$IF\ x_1 \text{ is } \widetilde{A}_1^l \ldots \text{ and } x_n \text{ is } \widetilde{A}_n^l \text{ THEN } y \text{ is centered } at\ y^{(t_u^l)} \quad (15)$$

Where $u = 1, \ldots, N$ and t_u^l is the data points index of Group l. The weighted average of all rules involved in the conflict group is subsequently calculated as shown below:

$$av^{(l)} = \frac{\sum_{u=1}^{N_l} y^{(t_u^l)} wi^{(t_u^l)}}{\sum_{u=1}^{N_l} wi^{(t_u^l)}} \quad (16)$$

These N_l rules are combined into a single rule, utilising the following format [17], [25], [26]:

$$IF\ x_1 \text{ is } \widetilde{A}_1^l \ldots \text{ and } x_n \text{ is } \widetilde{A}_n^l \text{ THEN } y \text{ is } \widetilde{B^l} \quad (17)$$

Where there is the selection of the output fuzzy set $\widetilde{B^l}$ based on the following: amongst the V_o output interval type-2 fuzzy sets $\widetilde{B^l}, \ldots, \widetilde{B^{V_o}}$ find the B^{h*} such that [17], [25], [26]:

$$\mu_{\widetilde{B^{h*}}}^{cg}\left(av^{(l)}\right) \geq \mu_{\widetilde{B^h}}^{cg}\left(av^{(l)}\right) \quad (18)$$
$$\text{for } h = 1,2 \ldots, V_o$$

$\widetilde{B^l}$ is selected owing to the fact that B^{h*}, where $\mu_{\widetilde{B^h}}^{cg}$ is the center of gravity of the interval membership of $\widetilde{B^h}$ at $av^{(l)}$ as in Equation (12).

As can be seen from the above, data pairs of input-output, comprising multiple outputs, are handled by our system. Step 1 is recognized as being distinct in regard to the number of outputs associated with each rule; on the other hand, Step 2 provides straightforward expansion with the aim of enabling rules to encompass multiple outputs; for each output, the calculations detailed in Equations (16), (17) and (18) are repeated.

4) The Customization of Knowledge Delivery to Students

The fuzzy rules generated through the input and output data of students and the extracted membership functions facilitate the suggested system in terms of establishing and learning the characteristics and requirements of knowledge delivery to students. As such, the system is then in a position to make changes to the online learning environment with particular consideration to the requirements of students. The system actions are initiated through the examination and monitoring of student variables, which cause an impact to be felt by the online instructional environment, especially in regard to the learned approximation of students' individual preferences.The type-2 fuzzy adaptive educational system considered in this paper works as follows:

- The crisp inputs which encompass the characteristics of the student, detailed in the e-learning environment, are fuzzified into the input interval type-2 fuzzy sets (singleton fuzzification).
- The inference engine and rule base are activated, which creates the outputs (student needs) type-2 fuzzy sets.
- The inference engine outputs are processed by type-reduction to produce type-reduced sets.
- The type-reduced type-1 fuzzy outputs are then de-fuzzified to create crisp outputs
- The crisp outputs are then fed to the outputs.

5) The Adaptive Process for Selecting and Presenting the Right Content for the User

It is necessary for the proposed system to be able to adjust to the changing requirements and constantly expand the knowledge level and held various engagement level of the students by providing them with the possibility to modify their learning needs. The system will change its rules or apply new ones accordingly. In case of a given input, no rules fire from the rule base, (i.e. the rule's firing strength in Equation (14) $wi^{(t)} = 0$), the system will capture the system input and will capture the user preferred delivery to create a rule which can cover this uncovered input status. Thus the system will incorporate new rules when the state of the online learning environment monitored at that time is indeterminate, according to the present rules in the rules base (i.e. where none of the present rules are fired). In such an instance, new rules will be devised and added by the system, whereby the antecedent sets highlight the online environment's present input states, with the consequent fuzzy sets reliant on the current state of knowledge delivery preferences. For all of the input parameters x_s the fuzzy sets that provide membership values, where $\mu_{\tilde{A}_c^h}^{cg}(x_s^{(t')}) > 0$ are identified. As a result, this creates a number of identified fuzzy set(s), in the form of a grid, for each input parameter. From such a grid, there is the construction of new rules based on all individual combinations of successive input fuzzy sets. The consequent fuzzy set which provide the greatest value of membership to the student defined knowledge delivery needs (y_c) are accordingly chosen to act as the generated rule consequent. The fuzzy sets resulting can be established through conducting a calculation of the output interval memberships' center of gravity [17], [25], [26].

$$\mu_{\tilde{B}_c^{h*}}^{cg}(y_c) \geq \mu_{\tilde{B}_c^h}^{cg}(y_c) \quad (19)$$

For $h = 1, \ldots, W$ the $\tilde{B}_c$ is chosen as $\tilde{B}_c^{h^*}$ where $c = 1, \ldots, k$. This enables the gradual addition of new rules.

In case the user indicates a change of preference for the knowledge delivery at a given input status, the fired rules will be identified and the rule consequents will be changed (if more than two users signal the same knowledge delivery preference) as indicated by Equation (19). Thus, the fired rules are adapted to more appropriately reflect the updated knowledge delivery requirements of the students, considering the present state of the online learning environment.

The system proposed in this paper will adopt life-long learning through facilitating the adaptation of rules according to the knowledge delivery needs of students, which notably change over time, and in regard to the state of the online learning environment. Owing to the system flexibility, the fuzzy logic model learned initially may be effortlessly expanded in order to make changes to both new and existing rules.

VI. EXPERIMENT AND RESULTS

Various experiments were conducted on a sample of 15 students from Essex University. The experiments involved knowledge delivery for an online course of fuzzy logic and its associated areas such as mathematics and Java programming. The experiments commenced by giving all students the non-adaptive version of the system to study for half an hour; after which, their level of knowledge of Java programming, fuzzy logic and mathematics were examined. Six input variables were captured during the usage of the system which are: the scores for fuzzy logic, mathematics and Java, average engagement degree, the age and gender of the students. The average engagement degree for each student was measured using the Kinect camera (as shown in Fig. 6 and as explained in section V). Afterwards, the scores and results were revealed to the students so they could determine their preference and the right content for their level with their preferred learning style. Hence, the system recorded the students' preferences for knowledge delivery with 12 outputs related to the preferred level of difficulty and the time needed to study for the three subjects (Java, math and fuzzy logic). In addition, six dimensions of the Felder-Silverman learning style model (visual/verbal, sensing/intuitive and active/reflective) as indicated in TABLE I were used to obtain and capture the percentage of student preferences for each one of them [31]. After the students' inputs and outputs had been obtained, the students were divided into three 5-member groups. The groups were equally divided based on the students' previous knowledge and average degree of engagement to overcome the possibility of the effect of external factors on the evaluations of the systems, such as placing students with poor performance and low motivation in one group or vice versa. The first group studied the non-adaptive version of the system; the second studied a knowledge delivery system based on type-1 fuzzy logic; and the third studied the knowledge delivery system based on the applied interval type-2 fuzzy logic system.

Once the groups were equally divided and the type-1 and type-2 groups' input and output data were obtained in this phase, the type-2 fuzzy logic and type-1 models were constructed for each group using the linguistic variables and rules as explained in Section V (See Fig. 7 for one of the extracted interval type-2 fuzzy logic sets).The type-2 fuzzy sets were obtained to capture the uncertainty that signifies students' views concerning a particular linguistic label explaining the characteristics, preferences and requirements, while the type-1 fuzzy logic system uses a type-1 fuzzy set shown in yellow dashed lines in Fig. 7.

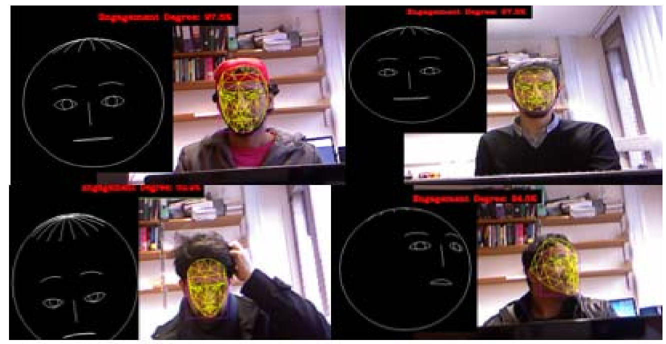

Fig. 6. Various participants with GUI of the vision engagement system

TABLE I. LEARNING STYLES CATEGORIES [31].

Learning Styles	Application in Online Courses
Visual / verbal	Visual learners prefer to acquire knowledge by using images, Graphics, charts, animation, and videos. Verbal learners prefer to acquire knowledge by using texts, audio.
Active / reflective	Active learners prefer to acquire knowledge by using self-assessment exercises, multiple-choice exercises. Reflective learners prefer to acquire knowledge by using examples, outlines, looking at results pages.
Sensing / intuitive	Sensing learners prefer to acquire knowledge by using examples, explanation, facts, and practical materials. Intuitive learners prefer to acquire knowledge by using definitions and algorithms.

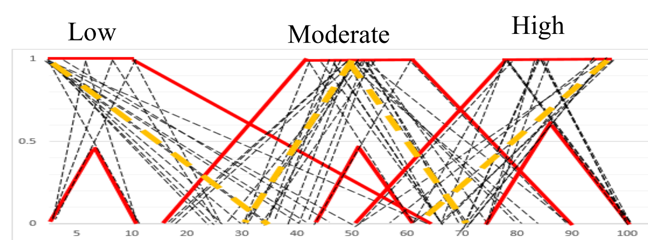

Fig. 7. The generated interval type-2 fuzzy sets of the average engagment level (think solid lines) and the type-1 fuzzy sets (thick dashed lines).

In the second phase, the course contents of the three subjects (Java, math, and fuzzy logic) were delivered as required for the second group that used the system based on type-1 fuzzy logic and the third group that used the system based on the applied interval type-2 fuzzy logic system. Meanwhile, the first group continued to study a non-adaptive version of the system. Thus, the second and the third groups were presented with individually tailored learning content matched to their preferences according to the rule base learnt from various similar system users. Users were presented with Learning Objects (LOs) according to their knowledge delivery needs. Each LO unit, such as arrays in Java, is associated with three linguistic values (as shown in Fig.7) corresponding to the difficulty of Java content and whether the user prefers to spend more time studying Java topics and its learning style type. There were more than 600 LOs for the three subjects (Java, Math and Fuzzy logic) which are ranged from very easy to very difficult content, and they covered all the learning styles categories that are theoretically described in TABLE I.(see Fig. 8) [31]. Once this phase was complete, students from the three groups were asked—after sufficient study time—to retake the previous tests with the aim of measuring the suggested system's overall efficiency in terms of improved learning outcomes and average degree of engagement which was measured using the Kinect camera (as shown in Fig. 6 and explained in section V) during each half hour for each student in the three groups.

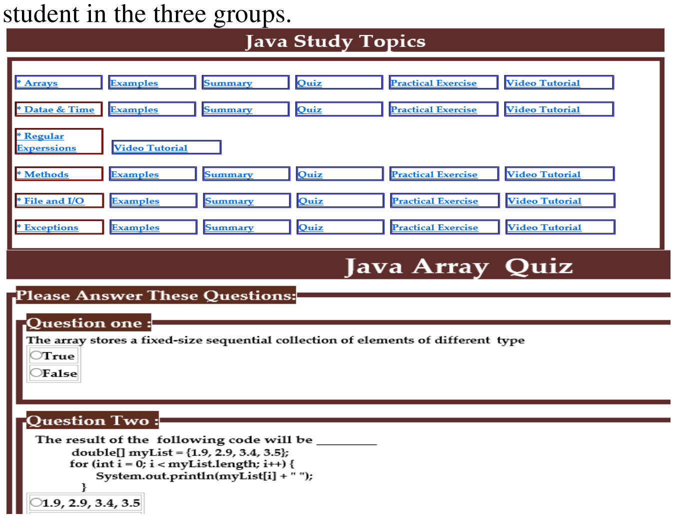

Fig. 8. Screenshots of various sample java study masteries

The results from the knowledge delivery system based on the applied interval type-2 fuzzy logic system were compared with those from the knowledge delivery system based on type-1 fuzzy logic and with those obtained from using the same knowledge delivery for all users (the non-adaptive version).Fig. 9 shows the improvements of the average scores obtained by each of the three different group's students in the three tested subjects (Java, math and fuzzy logic) prior to and after the application of the system using type-1 and type-2 fuzzy logic techniques and the non-adaptive version. As clearly shown in Fig. 9, there is a significant increase in fuzzy logic, Java and mathematics average scores due to the employment of the type-2 fuzzy logic system, which gave a better performance than both the type-1 fuzzy logic based system and the non-adaptive based system. In addition, the average engagement degree obtained for the three groups shown in Fig. 10 illustrates that the students engage more with the interval type-2 adaptive educational systems than with the type-1 fuzzy system and the non-adaptive based system. The improvements in the students' learning outcomes and average engagement degree evidence the effectiveness of the proposed interval type-2 adaptive educational systems compared to the type-1 fuzzy system and the non-adaptive based system. TABLE II. shows the average error and standard deviation for some of the system outputs (due to the space limitations we present only some of the outputs) obtained regarding the students' learned data. These results demonstrate that the type-2 fuzzy logic system produces a lower average and standard deviation of errors than the type-1 fuzzy logic system between the system output and the user desired output. This means that the type-2 system is more effective at capturing student behaviour.

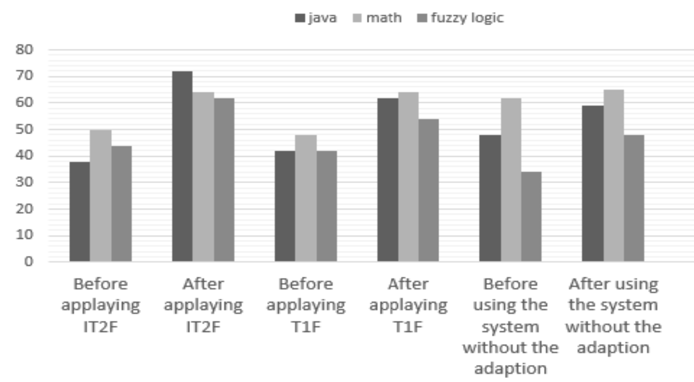

Fig. 9. The improvements of the average scores

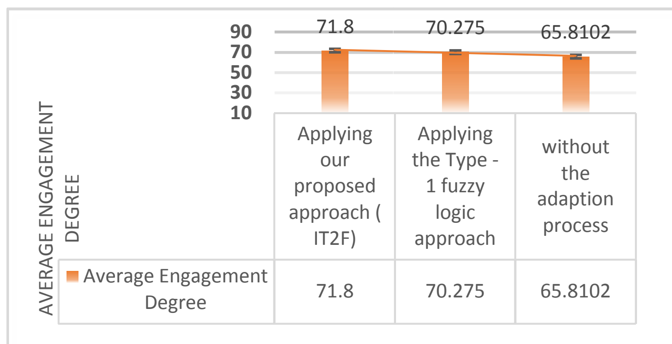

Fig. 10. The improvements of the engagements level

TABLE II. AVERAGE ERROR AND STANDARD DEVIATION OF SOME OF THE SYSTEM OUTPUTS

	Type 2 fuzzy logic		Type 1 fuzzy logic	
Output Name	Average error	Standard deviation	Average error	Standard deviation
Level of difficulty score for studying fuzzy logic	**1.33**	**0.83**	**2.65**	**2.59**
Needed time score for studying fuzzy logic materials	**2.11**	**0.96**	**2.31**	**2.20**
preference strength for active materials	**1.66**	**1.17**	**2.30**	**1.83**
preference strength for intuitive materials	**2.01**	**1.22**	**2.11**	**1.74**

VII. CONCLUSIONS

This paper presented an interval type-2 fuzzy logic-based system that can learn users' preferred knowledge delivery needs and learning style based on students' characteristics and engagement levels to generate a customized learning environment, resulting in enhanced student performance and engagement. For capturing the engagement levels of students, a method was proposed to utilize visual information to automatically calculate the engagement degree. This differs from traditional methods which usually employ expensive and invasive sensors. The presented type-2 fuzzy model was first created from data acquired from a number of students of differing capabilities and learning needs. The model was subsequently utilized in order to enhance knowledge delivery to the individuals based on their characteristics and engagement level.The proposed system is able to adapt and respond to the requirements of students continuously and on an individualized basis. Furthermore, the type-2 fuzzy logic-based model created is a white box model which can be easily read and interpreted.

The effectiveness of the proposed system has been evaluated through several real-world experiments with 15 students. The experiments revealed the ability of the proposed type-2 based system to handle the linguistic uncertainties, resulting in enhanced performance in terms of better user engagement and improved learning compared to type-1 based fuzzy systems and non-adaptive systems.

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