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PARSAT: Fuzzy logic for adaptive spatial ability training in an augmented reality system

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Abstract. Personalized training systems and augmented reality are two of the most promising educational technologies since they could enhance engineering students' spatial ability. Prior research has examined the benefits of the integration of augmented reality in increasing students' motivation and enhancing their spatial skills. However, based on the review of the literature, current training systems do not provide adaptivity to students' individual needs. In view of the above, this paper presents a novel adaptive augmented reality training system, which teaches the knowledge domain of technical drawing. The novelty of the proposed system is that it proposes using fuzzy sets to represent the students' knowledge levels more accurately in the adaptive augmented reality training system. The system determines the amount and the level of difficulty of the learning activities delivered to the students, based on their progress. The main contribution of the system is that it is student-centered, providing the students with an adaptive training experience. The evaluation of the system took place during the 2021-22 and 2022-23 winter semesters, and the results are very promising.

Keywords: Fuzzy logic, augmented reality, spatial ability, adaptive training, personalized system.

1. Introduction

All technologically enhanced realities fall under the broad concept of Extended Reality (XR), which combines the experiences of augmented reality (AR), virtual reality (VR), and mixed reality (MR) [1]. To improve this experience, AR overlays virtual content on top of the already existing real-world environment [2]. Contrarily, VR immerses viewers in an entirely new environment that is often developed and rendered by computers [3]. Finally, MR is a user environment that combines digital content and physical reality in a manner that makes it possible for users to interact with both real-world and virtual objects [4].

A user's perspective of the real world is altered through AR technology [2], [5]. Digital input, such as visual components, are used to create an improved version of the real world, which is delivered through technology. User-friendly AR applications offer a straightforward and enjoyable form of human-computer interaction. AR has been used into a wide range of industries, and it has especially great potential in educational settings, more particularly, in the training of engineers [6].

In order to improve engineering students' design skills, it is essential for engineering education to enhance students' spatial ability [7]–[9]. Numerous studies have investigated how using AR technology might support students become more efficient at technical drawings and develop their spatial skills, both of which are important for their academic work and potential professions [10]–[13]. Even though many researchers have explored the integration of AR in spatial ability training, no study has specifically developed a personalized AR spatial ability training system, which takes the student profile into account [14].

For greater educational outcomes, a training system should, nevertheless, be adaptable to the various students' individual needs. As a teacher would do in an in-person approach in a real classroom, the training system should also be able to periodically change the teaching technique and instructional approach in light of the student's needs. As a result, designing an adaptive learning system that satisfies the demands of the students might be challenging, since each student has unique learning needs and preferences [15].

Fuzzy logic developed by [16] can help with this challenge, as it is able to deal with ambiguity and inaccurate data. Knowledge level, in particular, is a concept that cannot be described as a variable that accepts distinct values, since learning is a complex process. In order to better accurately depict the learner's knowledge level, fuzzy sets and fuzzy logic may be employed. Since fuzzy logic techniques can deal with the uncertainty in data concerning students' cognitive state and behavior, they can be utilized to enhance the effectiveness of training systems.

The primary goal of the research, as stated in this paper, is to propose a spatial ability training system that helps students in learning technical drawing. The system incorporates every knowledge domain found in a conventional course curriculum. Our research is innovative in that it combines adaptive learning strategies with learning theory to offer students individualized learning activities within the context of spatial ability training, utilizing augmented reality.

Fuzzy sets are used each time to represent the knowledge level of the students. The assignments and training flow are then determined by the system. The training system specifically considers the student's progress, each time it has to select which learning activities need to be dynamically supplied to the student.

Particularly, the training system determines the length and complexity of the video tutorials that constitute each chapter, which in turn determines the quantity and difficulty of the learning activities and the evaluation questions. As a result, the student receives more personalized training using fuzzy logic techniques, which select the questions to be delivered to the student in the training's upcoming evaluation questions, based on the test results as input. In addition, the student receives a more individualized training experience due to AR characteristics which are dynamically shown in accordance with the student's progress and requirements.

The paper's contribution is as follows:

- **Contribution to intelligent tutoring systems:** The use of fuzzy logic and the Mamdani inference system allows for the incorporation of imprecise and uncertain information in decision-making, which can lead to more accurate and personalized feedback for the learners. The use of fuzzy weights further allows for the weighting of different factors in the decision-making process, depending on their relative importance. Together, these techniques enable PARSAT to provide personalized support for learners based on their individual needs and progress.

- **Contribution to domain knowledge model:** The integration of educational taxonomies, augmented reality technology, and intelligent tutoring systems can help to create a more engaging and effective learning environment for students.
- **Contribution to student modeling:** The integration of fuzzy logic and AR technology offers a promising avenue for developing personalized training systems in the domain of spatial skills training.
- **Contribution to electronic assessment:** The study does contribute to the collection of data on student performance during the training session. The proposed system collects information on the number of errors made by students during assessment tasks, which is an important metric for evaluating performance and providing personalized feedback. By tracking this data and using it to adjust the difficulty and amount of learning activities, the system can provide a more tailored and effective training experience for engineering students [17].

The structure of this paper is as follows. The literature review, regarding AR and adaptivity, is examined in Section 2. The description of the training system is presented in Section 3. The enhancement of the domain knowledge using taxonomy is discussed in Section 4. The modeling of students' knowledge through fuzzy logic is presented in Section 5. Experimental results obtained from training and the outcome of the system's evaluation are presented in Section 6. Finally, in Section 7, the work is concluded and continues with restrictions and future work.

The present paper is an extended and revised version of our preliminary conference paper that was presented in [18]. This paper significantly expands the evaluation of the proposed adaptive AR training system.

2. Literature Review

Various studies have been conducted examining the use of AR technology in domains such as education [19], [20], healthcare [21], [22], tourism [23], [24], culture [25], marketing [26], [27], industry [28], [29], all of which highlighted the impact that AR technology had. Their main objective is to keep users motivated and interested in the subject by providing them a pleasant experience. An AR application, called adaptive AR, offers useful and effective real-time information based on the user's specific features, interests, and context [30].

In [31] the authors introduced the concept of plasticity of augmentations and defined it as the ability of human-computer interaction (HCI) interface to fit the context of use defined by the user, the environment and the platform. The study evaluated adaptive AR by taking into consideration the size of augmentations, the illumination level of the scene, and the ambient noise. More specific, the system modifies the scale of the augmented object based on distance, adjusts the scene's luminosity to match ambient lighting, and levels the sound based on background noise.

In [32] the authors recognized adaptive behavior as the main challenge in developing AR systems, especially in the case of systems which provide information to the end users. The authors presented the trend inside the research community to develop techniques for better adaptation of the form and size of information that will be delivered to the users. Such systems have numerous challenges in identifying the user's behavior, determining in real-time what kind of adaptation to perform, so that it continuously adapts the AR content to the user's interest.

In [33] a user interface (UI) was presented, based on AR with head-mounted display (HMD), for increasing situational awareness during critical operations and improve human efficacy. The interface allowed the user to control a swarm of drones in order to explore the outside world, by presenting information in a virtual environment using 2D and 3D widgets. The research findings indicate that AR has the potential to increase human productivity and the success of mission-critical tasks.

In [34] the authors address how adaptation in AR could enable 3D objects to have their contrast adjusted to the degree of the ambient lighting of the environment. Now that mobile phones have sensors built in, mobile AR can become more adaptive, taking advantage of their built-in sensor modules which can be used to gather information about the user, the surrounding, and the device.

Explicit modalities, according to [35], are techniques that allow the system to receive input from users through gesture, speech, and touch. Information about changes at the environment (such as temperature, noise, and light) and changes at the device (such as orientation) are known as implicit modalities. A user's present location, for instance, can trigger a POI, based on the GPS sensor, while in order to provide a clearer view on the screen in low-light environments, the screen illuminance will be raised. Depending on the mobile device's orientation, the AR display screen can be changed.

In [36] the authors carried out research to enhance the knowledge provided to museum visitors, based on their emotional state at the time of their visit. Sensors are utilized to track visitor engagement and interest levels in order to adapt the experience. Their work has completely changed the way that adaptive AR approaches cultural heritage.

Even while adaptivity is significant and has a good impact on users, there are not many examples of educational systems that employ it. Only a few educational adaptive systems exist, however there is not an adaptive AR application for training students' spatial skills. As a result, an educational AR system that uses a different model to evaluate the student's cognitive state and makes the proper adjustments can be useful. The process of learning is multifaceted, and user's level of knowledge is an intangible concept. Knowledge is not a variable that can take on discrete values, and therefore, it is not accurate to claim if a domain concept is either known, or unknown. Fuzzy logic can be used to solve issues involving non-measurable entities [16].

As a result, fuzzy logic appears to be the best method for describing the students' level of knowledge. Adaptive tutoring systems have employed fuzzy logic, however spatial ability training systems have not. In light of this, we present a personalized AR training system that includes a cutting-edge module that employs fuzzy logic to develop student models, and provide on-the-spot modifications to the learning path's flow.

As a testbed for our research, we developed a personalized mobile application, namely PARSAT, for the training of spatial skills. PARSAT offers adaptivity regarding students' preferences, plus it creates a learning environment providing individualized learning activities that assure the training quality. PARSAT was used by university students and the results were really encouraging. The main difference, between PARSAT and the existing AR applications, is that the educational process is adaptive

[37], [38]. The basic idea of the application is to deliver relevant content, based on student's current level of knowledge [39].

3. Description of the System

The research described in the current paper involves the implementation of the novel approach of a spatial ability training system, incorporating fuzzy logic for the automatic recognition of the students' knowledge level, and augmented reality digital technology for the spatial ability training. Specifically, an innovative mobile environment for spatial skills training, namely PARSAT, has been developed. A set of hardware and software components, along with data that describe the real world and virtual content, form the basis of the augmented reality system. Fig. 1 presents the architecture of PARSAT, which is structured in three layers, as follows: the hardware is in the upper section, the software is in the middle, and the data is in the lower half.

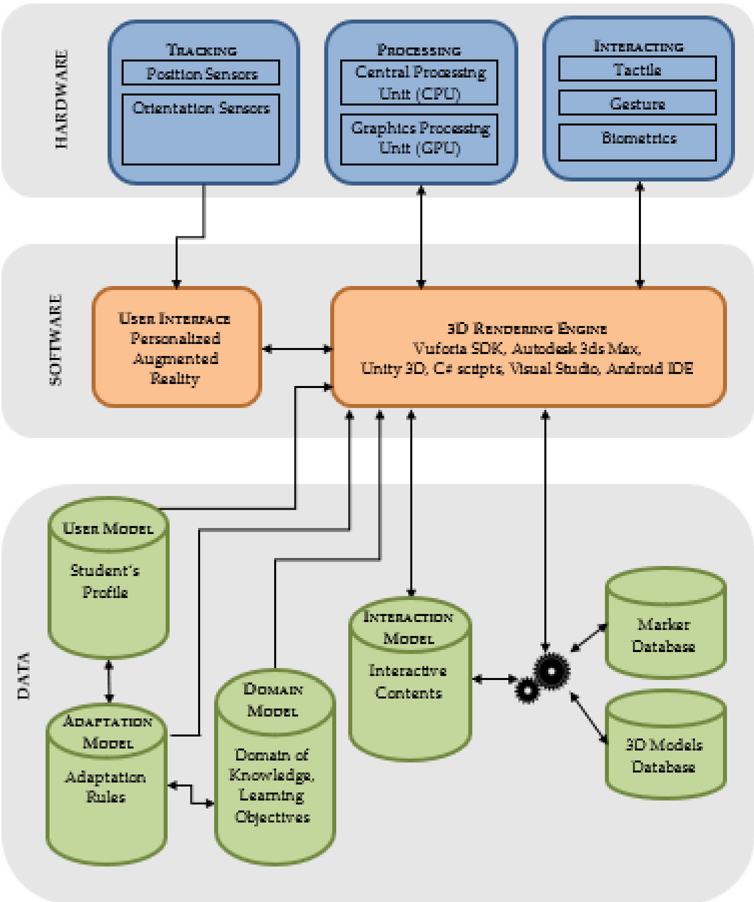


Fig. 1. The architecture of PARSAT

3.1. Hardware Layer

The tracking module consists of a range of sensors, such as accelerometer, gyroscope, magnetometer, and GPS, which determine the position and the orientation of the system, so that the virtual information will be in-line with the physical environment. Almost all mobile devices (smartphones and tablets) incorporate most of the aforementioned sensors.

The processing module consists of the fuzzy inference system, the 3D rendering, and overall, the system's user interface, are computational processes, and as such, they require significant hardware resources. To this purpose, all mobile devices embed powerful processing units. The graphics processing unit of mobile devices is specifically designed to accelerate the image output to a display, while the central processing unit of the mobile devices executes all the tasks and instructions from the user.

The interacting component incorporates a range of sensors, such as tactile surfaces, gesture recognition, and biometrics, which translate the user's interaction with the system. Tactile sensor is integrated in PARSAT, so that the identified information is due to the contact of the student's fingers on the mobile screen. All mobile devices support touch commands, which are identified by key components, such as a tactile sensor.

3.2. Software Layer

A user interface's success is determined by how discretely people may use it, without interruptions from other interface components. In the context of AR applications, this is also accurate. Due to AR's immersive and captivating nature, PARSAT's user interface aims to focus on how students engage with the system. It is achieved by focusing on the five essential User Interface (UI) – User Experience (UX) AR pillars [40]–[42] as listed below:

- Environment: for AR design, the environment in which users will interact with the application, must be considered. Everything is included, from the lighting to the actual area where users are positioned. In the case of PARSAT, students used the application in their university laboratories, which are organized taking into consideration the best user ergonomics and safety.
- Interaction design: this parameter is also crucial, as the interaction design determines how the user interacts with the context of PARSAT. The main gestures that are used to manipulate the application, and make the most of the AR experience, are: a) tapping, which is performed with a light touch of student's finger, and it is used for pressing buttons and selecting, b) double tapping, which is used to zoom in on the 3D models, c) pinching, which needs two fingers close together, or spread apart, to adjust the size of the 3D models, and d) rotating, which is the basic gesture for the understanding the spatial geometry of the 3D models from different perspectives, and revealing their hidden views.
- Colors: the science of color theory applies to AR, just as it does to print, mobile, and the web. PARSAT's colors are acceptable for its educational scope. The text is visible, and fonts are appropriate, so the student find it simple to read. Depending on the situation, San Serif fonts may be simpler to read than Serif fonts. The optimum contrast schemes for reading are selected using light text on a dark background.
- Feedback: it is a critical parameter which is considered, defining how students will be informed of their activities and the results or outcome of those actions. Whether it is the feedback on the assessment score, or feedback encouraging the student to continue the effort on training, it is a parameter which adaptive systems usually integrate.

The 3D rendering engine is a combination of the software integrated in the PARSAT application. More specific, this engine maintains an internal 3D representation of the virtual scene augmenting the real world.

This internal representation is updated in real-time according to several factors such as the user's profile, student's interactions, the 3D objects behavior, the updated knowledge domain, and the fuzzy inference adaptation. Both, hardware components such as the CPU and the GPU, and data components, are dedicated to the 3D rendering engine for the creation of the user interface screens.

PARSAT is implemented using Unity 3D cross-platform game engine, v. 2020.3.43f1 LTS, Vuforia Software Development Kit (SDK), Autodesk 3ds Max 2020, scripts in C# programming language, Visual Studio 2019, and Android Studio Integrated Development Environment (IDE).

3.3. Data Layer

PARSAT integrates marker-based AR, requiring a trigger image or a QR code to activate the AR experience. The student detects and scans the marker using the mobile device's camera, the image is identified as a marker, and then, the device renders the virtual content on top of the marker. This feature allows the student to move around the marker and observe the perspectives of the 3D content.

Cloud-based or device-localized are the two categories of marker-based AR. In the first category, since the AR assets must be downloaded from the server, a cloud-based AR experience may require a few additional minutes to load. In the second category, since the AR assets have already been pre-downloaded to the student's mobile device via the application, a localized AR experience may be accessed instantly. For greater storage capacity, the choice of the cloud-based AR is preferred, but localized AR is less expensive and not dependent on network availability. PARSAT integrates localized marker-based AR.

The marker-based AR experience is created using a software development kit (SDK), namely Vuforia, one of the best-known AR tool sets, which adds advanced computer vision functionality by creating AR experiences that realistically interact with the 3D geometrical objects displayed at each level, supporting a broad range of devices, not only Android and iOS smartphones and tablets, but also AR headsets, such as Microsoft Hololens and Magic Leap.

The 3D models database is crucial, as the students interact with the virtual models to train their spatial visualization skills. 3D modeling software options are separated into two main categories, the first one is the free and the second category is the license-paid software.

The effective selection of 3D modeling software depends on the objects which are to be designed, the interface of the software, the community behind the software offering tutorials, step-by-step guides, and commonly asked questions, and, in case of a paid license, the actual cost of the product. PARSAT's 3D models database is prepared using Autodesk 3ds Max.

4. Enhancing Domain Knowledge with SOLO Taxonomy

In this section, the training system's domain knowledge is presented, considering the Structure of Observed Learning Outcomes (SOLO) taxonomy. The content of the domain model is a critical component of the application's structure, whereas the combination of the learning theory with adaptive learning activities enhances the students' motivation and improves their learning outcome.

4.1. Domain Model

The content of the domain knowledge is consisted of three levels, covering the topic of the Technical Drawing (TD) course, and its objectives in detail, as follows:

- Recognize the exploratory potential of technical drawing while acknowledging the universality of objective language in information transmission and comprehension.
- Strengthen the skills necessary for them to represent graphical solutions precisely and objectively.
- Have a basic understanding of technical drawing so that students can utilize it to read and interpret simple designs and artistic creations as well as to develop well-thought-out solutions to mathematical challenges in both the plane and space.
- Recognize normalization as the optimum realist for condensing communication and giving it a more universal tone.
- Include technical drawing tasks in a study area where aesthetic considerations are relevant, such as art, architecture, or industrial design.
- Recognize and depict shapes in accordance with ISO standards.
- Recognize how different approaches enhance the traditional idea of technical drawing.
- Include the information provided by technical drawing in technological, artistic, or scientific research process.
- Encourage method and rationality in sketching, as a way to convey scientific and technological concepts.
- Acquire abilities that enable the expression of graphical solutions with accuracy, clarity, and objectivity.
- Skillfully employ the specialized tools of technical drawing, and pay attention to the drawing's proper execution, as well as the enhancements that various graphical styles can provide to the depiction.
- Master the art of sketching to improve the speed and accuracy while expressing graphically.
- Connect the space to the plane, recognizing the requirement to complete exercises from the activity book.

4.2. Domain Knowledge Alongside SOLO Taxonomy

SOLO taxonomy was created, within a constructivist context, as a tool for teaching students how to use basic rubrics to think more thoroughly about their own understanding. In addition to evaluation, SOLO is used in the developed system to design the curriculum according to the expected level of learning outcomes, which helps in establishing constructive alignment.

PARSAT has used the SOLO taxonomy in the development of the assessment items for the learning objectives in technical drawing. These items had to fit to curriculum's objectives and levels, and measure both surface and deep cognitive states. Throughout the PARSAT development, experienced faculty members in the field of technical drawing have been involved in designing and reviewing the assessment tasks according to the SOLO taxonomy. Table 1 illustrates the learning goals and the corresponding activities per SOLO level.

Table 1. Learning goals and activities per SOLO level [43], [44]

SOLO level	Learning goal	Learning activities	Description of the activities
Pre-structural (L1)	Students get information on the subject	1. Define concepts 2. List items 3. Match information 4. Name facts	Introduction to Technical Drawing: A history and current importance of drawing are presented Students are asked to illustrate the significance of drawing by presenting applications and reports of both good and negative uses of the skill
Unistructural (L2)	Students define, recognize, name, sketch, reproduce, recite, follow simple instructions, calculate, reproduce, arrange, find	5. Identify content to be memorized, show examples 6. Provide disciplinary context 7. Mnemonics in groups 8. Repetition of procedures 9. Games 10. Repetitive testing and matching 11. Peer testing (one student asks, one answers)	Setting up a model space in CAD software by defining limits, grid, snap, layers, and object snap Video tutorials on standard views, views' alignment, completion of activity sheet, and setting up the model space Border creation with a completed title block to be used for all future drawings, and drawing templates with all the settings necessary saved within it
Multi-structural (L3)	Students describe, list, classify, structure, enumerate, conduct, complete, illustrate, solve	12. Glossaries of key terms with definitions, classifications, examples to build disciplinary vocabulary 13. Simple laboratory exercises 14. Define terms, compare to glossary 15. Games modelled on Trivial Pursuit, Family Feud	Orthographic drawing creation Lines, layers Isometric object drawing Video tutorials on linetype, lineweight and isometric drawing creation of objects in the activity
Relational (L4)	Students relate, analyze, compare, integrate, plan, construct, implement, summarize	16. Case studies, simulations, and complex lab exercises 17. Concept maps 18. Research projects and experiential learning cycles 19. Application of theoretical models 20. Reflective journals 21. Student seminars and debates 22. Syndicate groups (each group is part of whole) 23. Problem-Based Learning and Inquiry Learning	Scaling the border and title block to fit the orthographic drawing Dimensioning an orthographic drawing Video tutorials on basic dimensioning rules and parts of dimensions Filling in a title block, including Name, Date, Title, Drawing No., and the correct scale Snapping and Text commands
Extended abstract (L5)	Students generalize, hypothesize, theorize, predict, judge, evaluate, assess, predict, reason, criticize	24. Self-directed projects involving research, design, application, argumentation, evaluation 25. Case studies involving extensive analysis, debate, reflection, argumentation, evaluation, forecasting 26. Development of a theory or model 27. Experiential learning cycles 28. Problem Based Learning and Inquiry learning	Printing the drawing on 8.5" × 11" paper (letter size) in landscape orientation Video tutorial on cutting plane, half and full sections Printer/plotter settings Export/plot an object that has been drawn in CAD so it can be exported or printed to a variety of other applications CAD software to create objects that are more precise and sometimes easier to draw in CAD than in other software

4.3. Examples of learning activities of each SOLO level

A simple uni-structural assignment is presented in Fig. 2, while the student must observe the object in 3D, place herself/himself on the spot that the black arrow points to, and identify the object’s front view in 2D, ignoring the other views, and following simple procedure of the general principles of graphical representation of objects on technical drawings.

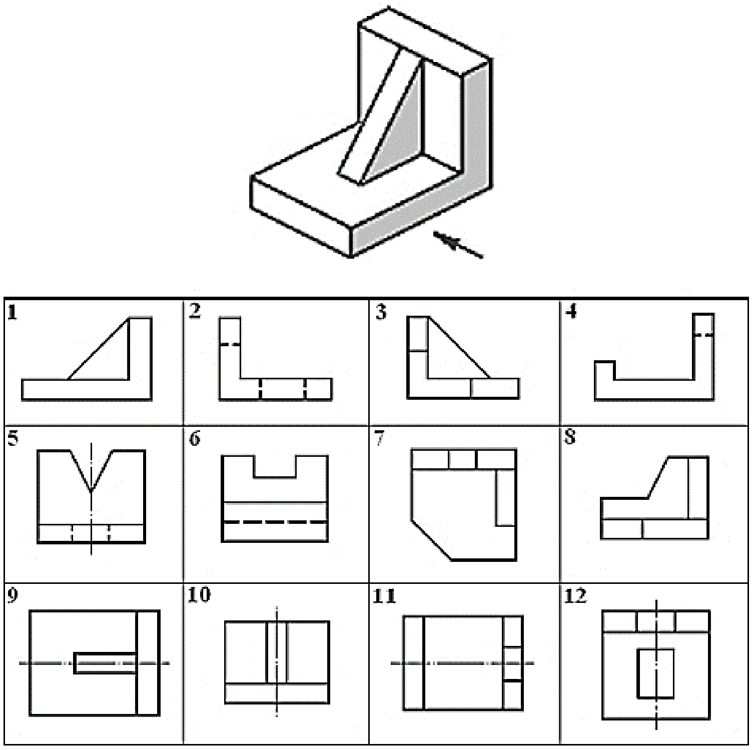
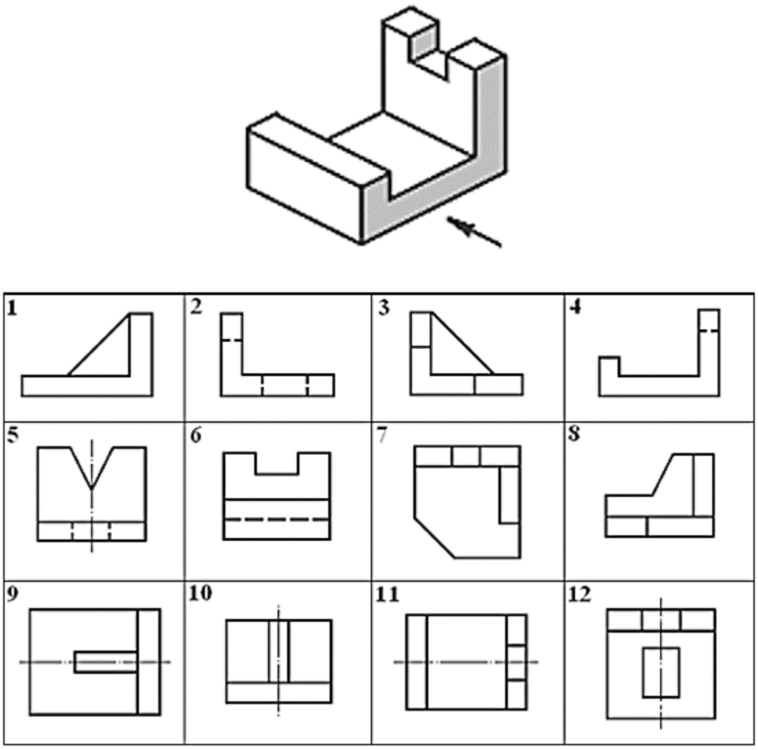


Fig. 2. Sample activity of uni-structural SOLO level

In the assignment of the relational SOLO level of Fig. 3, the students would need to analyze the individual views of the object and consider how they relate to one another. They would need to identify key features and elements in each view and determine how they fit together to create a complete picture of the object's structure and geometry.

Students would also need to think critically about the limitations of each view and consider how they might be used together to overcome these limitations. For example, the front view might provide a clear representation of the object's height and width, while the top view might be better for showing its depth and overall shape.

Overall, this assignment requires students to engage in higher order thinking and consider the relationships between different pieces of information to create a more integrated and holistic understanding of the object.



Answers	
Front view	
Top view	
Left-side view	

Fig. 3. Relational level question of SOLO taxonomy

5. Modelling the Knowledge of Students with Fuzzy Logic

In this section, the principles of the design of the student model, within the spatial ability training platform, are discussed. The model allows steering of the sequence of the educational material and the deliverable learning activities, through the incorporation of fuzzy logic, quantitative inputs, and fuzzy weights.

5.1. Fuzzy Logic Algorithm

The student model, which may be found in most of the latest adaptive educational software [45], is responsible for defining the student's knowledge level. The purpose of the student model is to represent the students' current level of knowledge [37], and it is essential for the system to provide the necessary level of customization on every student's learning requirement. Other approaches regarding adaptivity, are those of neural networks, machine learning, fuzzy logic networks etc., which can be utilized to build the student model [46]. The backbone of PARSAT’s student model is fuzzy logic, which defines the students' current level of knowledge.

PARSAT’s fuzzy system consists of three main parts: a) the part of the linguistic variables, b) the part of the membership functions, and c) the rules. This section describes the general process of designing the fuzzy system.

The process of developing the fuzzy system starts by defining the linguistic variables, which represent, in words, the system’s input and output variables. Each linguistic variable is described by a specific number of linguistic values, while in most cases three to seven terms are enough.

The proposed fuzzy model has four inputs, namely prior knowledge (PRK), video-based learning duration (VLD), augmented-reality interaction duration (ARID), and number of errors (NoE). The first input is derived from the student profile, while the remaining three inputs are derived from the interaction model. Furthermore, the output value and its linguistic name is the current knowledge level (CKL). Table 2 presents the input linguistic variables and their ranges.

Table 2. Linguistic input variables and their ranges

Linguistic Variable: Prior Knowledge (PRK)		
Linguistic Value	Notation	Range (normalized)
Poor	PRK_PR	[0, 0.35]
Medium	PRK_MDM	[0.30, 0.75]
Good	PRK_GD	[0.70, 1.00]
Linguistic Variable: Video-based Learning Duration (VLD)		
Linguistic Value	Notation	Range (normalized)
Short	VLD_SRT	[0, 0.35]
Normal	VLD_NRML	[0.30, 0.70]
Long	VLD_LNG	[0.60, 1.00]
Linguistic Variable: Augmented-Reality Interaction Duration (ARID)		
Linguistic Value	Notation	Range (normalized)
Short	ARID_SRT	[0, 0.60]
Normal	ARID_NRML	[0.40, 0.80]
Long	ARID_LNG	[0.70, 1.00]
Linguistic Variable: Number of Errors (NoE)		
Linguistic Value	Notation	Range (normalized)
Small	NoE_SMLL	[0, 0.40]
Medium	NoE_MDM	[0.35, 0.65]
Large	NoE_LRG	[0.60, 1]

5.2. Fuzzy Sets

At the second part, fuzzy sets are determined. All input values are mapped into fuzzy ones using the membership functions. We integrated membership functions, which are formed using straight lines, having the advantage of simplicity, and more specific the trapezoidal membership function. A trapezoidal membership function is assigned to each linguistic variable. A curve with four points (a, b, c, d) representing a lower limit (a), an upper limit (b), a lower support limit (c), and an upper support limit (d) is known as a trapezoidal membership function. The curve's values range from 0 to 1. Real values between b and c are represented by degree of membership 1. Values between a and b have a higher degree of membership as they move closer to element b, whereas values between c and d have a lower degree of membership as they move closer to element d. The membership degree is zero in all other cases.

The student's video-based learning duration of each topic is recorded in seconds, and the current level's cumulative sum is normalized, resulting in the values of the linguistic variable of this input, namely short (VLD_SRT), normal (VLD_NRML) and long (VLD_LNG) (Fig. 4).

$$\mu_{VLD\_SRT}(x) = \begin{cases} 1\,; & x \leq 0.20 \\ 1 - \dfrac{x - 0.20}{0.15}\,; & 0.20 \leq x \leq 0.35 \\ 0\,; & x \geq 0.35 \end{cases}$$

$$\mu_{VLD\_NRML}(x) = \begin{cases} \dfrac{x - 0.30}{0.10}\,; & 0.30 \leq x \leq 0.40 \\ 1\,; & 0.40 \leq x \leq 0.60 \\ 1 - \dfrac{x - 0.60}{0.10}\,; & 0.60 \leq x \leq 0.70 \\ 0\,; & x \leq 0.30 \; or \; x \geq 0.70 \end{cases}$$

$$\mu_{VLD\_LNG}(x) = \begin{cases} \dfrac{x - 0.60}{0.20}\,; & 0.60 \leq x \leq 0.80 \\ 1\,; & 0.80 \leq x \leq 1.00 \\ 0\,; & x \leq 0.60 \end{cases}$$

Fig. 4. Membership functions describing video-based learning duration

Another example is the variable of the fourth input, namely number of errors, which is defined by the average student's performance in the level's test, rated on a 100-point scale. The values of the linguistic variable are small (NoE_SMLL), medium (NoE_MDM) and large (NoE_LRG) (Fig. 5).

Figures 6 and 7 present the rest two input variables, namely prior knowledge, and augmented-reality interaction duration, which take the linguistic variables poor (PRK_PR), medium (PRK_MDM), good (PRK_GD) and short (ARID_SRT), normal (ARID_NRML), long (ARID_LNG), respectively.

The fuzzy system's output value, and its linguistic term, is the student's current level of knowledge (CLK), taking the values namely Novice (N), Beginner (B), Competent (C), Very Good (VG), Proficient (P), and Expert (E).

$$\mu_{NoE\_SMLL}(x)=\begin{cases}1\,; & x\leq 0.20\\ 1-\dfrac{x-0.20}{0.20}\,; & 0.20\leq x\leq 0.40\\ 0\,; & x\geq 0.40\end{cases}$$

$$\mu_{NoE\_MDM}(x)=\begin{cases}\dfrac{x-0.30}{0.10}\,; & 0.30\leq x\leq 0.40\\ 1\,; & 0.40\leq x\leq 0.60\\ 1-\dfrac{x-0.60}{0.05}\,; & 0.60\leq x\leq 0.65\\ 0\,; & x\leq 0.30\ or\ x\geq 0.65\end{cases}$$

$$\mu_{NoE\_LRG}(x)=\begin{cases}\dfrac{x-0.60}{0.20}\,; & 0.60\leq x\leq 0.80\\ 1\,; & 0.80\leq x\leq 1.00\\ 0\,; & x\leq 0.60\end{cases}$$

Fig. 5. Membership functions describing number of errors

$$\mu_{PRK\_PR}(x)=\begin{cases}1\,; & x\leq 0.20\\ 1-\dfrac{x-0.20}{0.15}\,; & 0.20\leq x\leq 0.35\\ 0\,; & x\geq 0.35\end{cases}$$

$$\mu_{PRK\_MDM}(x)=\begin{cases}\dfrac{x-0.30}{0.10}\,; & 0.30\leq x\leq 0.40\\ 1\,; & 0.40\leq x\leq 0.60\\ 1-\dfrac{x-0.60}{0.15}\,; & 0.60\leq x\leq 0.75\\ 0\,; & x\leq 0.30\ or\ x\geq 0.75\end{cases}$$

$$\mu_{PRK\_GD}(x)=\begin{cases}\dfrac{x-0.70}{0.10}\,; & 0.70\leq x\leq 0.80\\ 1\,; & 0.80\leq x\leq 1.00\\ 0\,; & x\leq 0.70\end{cases}$$

Fig. 6. Membership functions describing student’s prior knowledge

$$\mu_{ARID\_SRT}(x) = \begin{cases} 1\,; & x \leq 0.40 \\ 1 - \dfrac{x - 0.40}{0.20}\,; & 0.40 \leq x \leq 0.60 \\ 0\,; & x \geq 0.60 \end{cases}$$

$$\mu_{ARID\_NRML}(x) = \begin{cases} \dfrac{x - 0.40}{0.10}\,; & 0.40 \leq x \leq 0.50 \\ 1\,; & 0.50 \leq x \leq 0.70 \\ 1 - \dfrac{x - 0.70}{0.10}\,; & 0.70 \leq x \leq 0.80 \\ 0\,; & x \leq 0.40 \text{ or } x \geq 0.80 \end{cases}$$

$$\mu_{ARID\_LNG}(x) = \begin{cases} \dfrac{x - 0.70}{0.10}\,; & 0.70 \leq x \leq 0.80 \\ 1\,; & 0.80 \leq x \leq 1.00 \\ 0\,; & x \leq 0.70 \end{cases}$$

Fig. 7. Membership functions describing augmented-reality interaction duration

5.3. Fuzzy Rule Base

A set of linguistic statements, known as a fuzzy rule base, describes how PARSAT's fuzzy inference system makes decisions by classifying input, or controlling output. Fuzzy IF-THEN rules are used to aggregate all the variables, as there are input and output variables.

A set of 81 fuzzy rules were formulated, and they have been incorporated in the proposed system, which were specifically designed to create the logical outcome. The rest part of this subsection presents a representative sample of the aforementioned rules, showing how inputs affect the output.

Example Rule 1:

IF PRK is PRK_PR AND VLD is VLD_LNG AND ARID is ARID_LNG AND NoE is NoE_LRG THEN CLK is N

The aforementioned rule indicates that a student, with poor prior knowledge background, spending long time, both in watching the session's video tutorials (maybe by replaying them all the time, or constantly pausing and rewinding them) and in manipulating the 3D models through the AR environment (maybe finding it difficult to conceptualize their geometry), and finally scoring a large number of errors in the assessment section, then the user is classified as a novice student.

Example Rule 2:

IF PRK is PRK_GD AND VLD is VLD_NRML AND ARID is ARID_NRML AND NoE is NoE_SMLL THEN CLK is E

The above rule highlights a student who is an expert, while the main contributing factor is that the student has a good background in technical drawing, and the assessment's measured errors are small.

Example Rule 3:

IF PRK is PRK_MDM AND VLD is VLD_NRML AND ARID is ARID_NRML AND NoE is NoE_SMLL THEN CLK is P

The 3rd example of rule results in a proficient student, as the starting point is at medium level, but through training and personalized learning activities, managed to achieve excellent assessment score.

The next two rules consider the various inputs that all contribute to the knowledge level rating of the student being beginner.

Example Rule 4:

IF PRK is PRK_PR AND VLD is VLD_NRML AND ARID is ARID_LNG AND NoE is NoE_LRG THEN CLK is B

Example Rule 5:

IF PRK is PRK_PR AND VLD is VLD_LNG AND ARID is ARID_NRML AND NoE is NoE_LRG THEN CLK is B

The next rule indicates that spending normal time watching the educational tutorials and interacting with the virtual models, results in a competent knowledge rating.

Example Rule 6:

IF PRK is PRK_PR AND VLD is VLD_NRML AND ARID is ARID_NRML AND NoE is NoE_LRG THEN CLK is C

Example Rule 7:

IF PRK is PRK_MDM AND VLD is VLD_SRT AND ARID is ARID_NRML AND NoE is NoE_MDM THEN CLK is VG

Example Rule 8:

IF PRK is PRK_GD AND VLD is VLD_NRML AND ARID is ARID_SRT AND NoE is NoE_MDM THEN CLK is VG

Example rules 7 and 8 highlight a very good student, and case it when a student answers the assessment's evaluation test with normal number of errors.

5.4. Fuzzy Inference System

The fuzzy inference system (FIS) evaluates the rules saved the rule base and combines the results of each rule. The proposed system gets four inputs, namely prior knowledge, video-based learning duration, augmented-reality interaction duration and number of errors, fuzzified through the trapezoidal membership functions (Fig. 8).

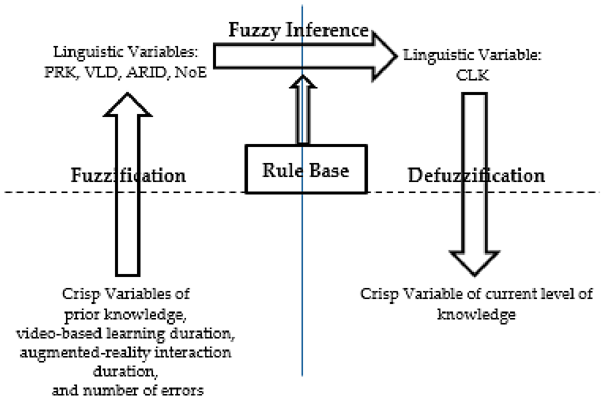


Fig. 8. Architecture of the fuzzy inference system

Then, 81 fuzzy rules were fed to the inference engine, in order to determine output, namely the student's current knowledge level. In this research, the Mamdani FIS [47] is employed, as it is typically used to capture expert knowledge. It enables us to communicate more naturally, while describing the expertise.

The fuzzy inputs must be combined into a single fuzzy output, by using the Mamdani inference engine's fuzzy implication. The fuzzy input variables for each of the rules are then connected using the AND operator. This operator's function is to extract the minimum membership function value from the fuzzy input variables. Using the value obtained from the input component, the fuzzy output variable is truncated. By taking the maximum value of the membership degree, the entire shortened output is therefore aggregated into a single graph and employed in the final stage of the fuzzy logic system.

5.5. Defuzzification

Defuzzifier procedure maps the fuzzy output to a crisp value according to the membership function of output variable. In order to get the crisp value, a diverse method is required. This defuzzification is not part of the "mathematical fuzzy logic" and various methods are possible [48]–[50]. The input for the defuzzification process is the aggregate output fuzzy set, while the output is a single number. The Center of gravity (COG) method is most prevalent and physically appealing of all the defuzzification methods [51], which was taken into consideration in this model, resulting the gravity center procedure to be applied in this study. The basic principle in COG method is a centroid approach, which finds the point where a vertical line slices the aggregate set into two equal masses.

5.6. Adaptation of the Learning Activities Based on Fuzzy Weights

Technical drawing assumes high level training of spatial ability, while it is achieved by using adaptive learning activities considering the student's level of knowledge. This is accomplished by converting student's current knowledge level to fuzzy weights to deliver appropriate learning activities both in quantity and level of difficulty, learning activities.

Six fuzzy weights have been defined in this approach to represent the current knowledge level of students in the domain of technical drawing. The membership functions which are used to calculate the sextet that best defines the student's current level of knowledge are presented in Fig. 9.

$$\mu_N(x) = \begin{cases} 1\,; & x \le 0.10 \\ 1 - \dfrac{x - 0.10}{0.10}\,; & 0.10 \le x \le 0.20 \\ 0\,; & x \ge 0.20 \end{cases}$$

$$\mu_B(x) = \begin{cases} \dfrac{x - 0.10}{0.10}\,; & 0.10 \le x \le 0.20 \\ 1\,; & 0.20 \le x \le 0.30 \\ 1 - \dfrac{x - 0.30}{0.10}\,; & 0.30 \le x \le 0.40 \\ 0\,; & x \le 0.10 \; or \; x \ge 0.40 \end{cases}$$

$$\mu_C(x) = \begin{cases} \dfrac{x - 0.30}{0.10}\,; & 0.30 \le x \le 0.40 \\ 1\,; & 0.40 \le x \le 0.50 \\ 1 - \dfrac{x - 0.50}{0.10}\,; & 0.50 \le x \le 0.60 \\ 0\,; & x \le 0.30 \; or \; x \ge 0.60 \end{cases}$$

$$\mu_{VG}(x) = \begin{cases} \dfrac{x - 0.50}{0.10}\,; & 0.50 \le x \le 0.60 \\ 1\,; & 0.60 \le x \le 0.70 \\ 1 - \dfrac{x - 0.70}{0.10}\,; & 0.70 \le x \le 0.80 \\ 0\,; & x \le 0.50 \; or \; x \ge 0.80 \end{cases}$$

$$\mu_P(x) = \begin{cases} \dfrac{x - 0.70}{0.10}\,; & 0.70 \le x \le 0.80 \\ 1\,; & 0.80 \le x \le 0.90 \\ 1 - \dfrac{x - 0.90}{0.10}\,; & 0.90 \le x \le 1.00 \\ 0\,; & x \le 0.70 \end{cases}$$

$$\mu_E(x) = \begin{cases} \dfrac{x - 0.90}{0.05}\,; & 0.90 \le x \le 0.95 \\ 1\,; & 0.95 \le x \le 1.00 \\ 0\,; & x \le 0.90 \end{cases}$$

Fig. 9. Membership functions describing student's knowledge level

The output of the aforementioned membership functions is limited to between 0 and 1, and they are used in the fuzzification and defuzzification steps of the fuzzy logic system, as they map the non-fuzzy input values to fuzzy linguistic terms and vice versa. We integrated membership functions which are formed using straight lines, having the advantage of simplicity, and more specific the trapezoidal membership function (Fig. 10).

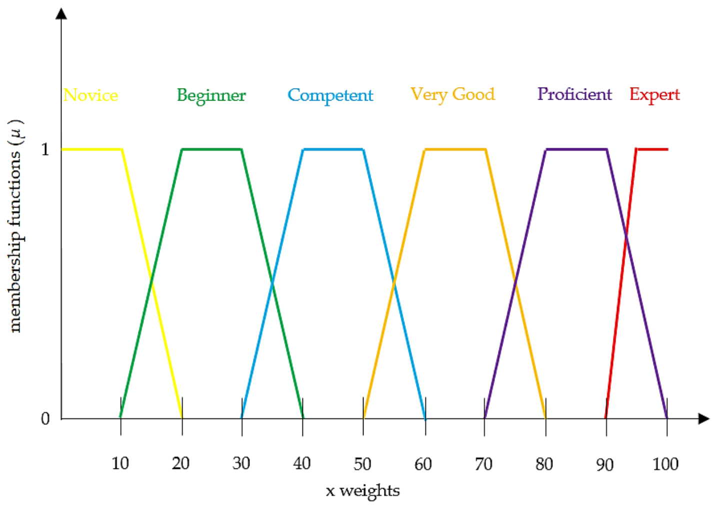


Fig. 10. Fuzzy weights of knowledge level in linguistic terms

Student's knowledge level is described by the sextet (N, B, C, VG, P, and E), and as such, the student may be fully assigned to one, or partially assigned to more fuzzy sets, meaning that student's knowledge level can be described as 'Competent' or partially 'Very Good' and partially 'Proficient', respectively. As an example, a student's sextet of (0, 1, 0, 0, 0, 0), classifies the student as 100% 'Beginner'. Another example of a student's sextet which is (0, 0, 0, 0.70, 0.30, 0), classifies the student to be 70% 'Very Good' and 30% 'Proficient'. But whatever the values of the sextet are, the equation $\mu N(x) + \mu B(x) + \mu C(x) + \mu VG(x) + \mu P(x) + \mu E(x) = 1$ stands.

In this section, the analysis of the rules, in combination with the fuzzy weights, is presented to adapt the teaching strategy to the students' knowledge level [52]–[54]. The number of learning activities of each level's chapter that the student must learn each time, is dynamically defined according to the current level of knowledge [55].

The rules' design plays an important role in determining the number and the difficulty of the learning activities delivered to the students. The rules have been defined by eight professors from the Department of Informatics and Computer Engineering, who utilized the fuzzy rules, and their related thresholds at the membership functions. The faculty members were asked to define, in more detail, the technical drawing knowledge levels that students gain during the course throughout the course of an entire semester. All the faculty members have more than 15 years of experience instructing technical drawing in academic contexts, and they can attest to the accuracy of the depiction of students' knowledge levels. They contributed to the current stage by matching each learning activity with the corresponding SOLO level.

As an example, a beginner student needs to study many topics of low difficulty of the initial levels of SOLO taxonomy, such as pre-structural and unistructural level, whereas an expert student can deal topics of the multi-structural and relational level of SOLO taxonomy of lesser quantity. The set of rules in total is presented in Table 3.

Table 3. Decision rules for adaptive instruction

Current level of knowledge	L1	L2	L3	L4	L5	Sum of LAs
$\mu_N = 1$	9	5	0	0	0	14
$\mu_N < 1$ and $\mu_B < 1$	8	5	0	0	0	13
$\mu_B = 1$	6	6	0	0	0	12
$\mu_B < 1$ and $\mu_C < 1$	5	5	1	0	0	11
$\mu_C = 1$	4	4	2	0	0	10
$\mu_C < 1$ and $\mu_{VG} < 1$	3	3	3	0	0	9
$\mu_{VG} = 1$	1	1	3	2	1	8
$\mu_{VG} < 1$ and $\mu_P < 1$	0	1	2	3	1	7
$\mu_P = 1$	0	0	1	4	1	6
$\mu_P < 1$ and $\mu_E < 1$	0	0	0	3	2	5
$\mu_E = 1$	0	0	0	1	3	4

According to Table 3, a student who was assigned a crisp output value of 76 per cent, has been classified as partially very good and partially proficient, and will be delivered learning activities (LAs), as follows:

- no learning activity of SOLO-L1;
- one learning activity of SOLO-L2;
- two learning activity of SOLO-L3;
- three learning activities of SOLO-L4; and
- one learning activities of SOLO-L5.

6. Evaluation and Discussion

The evaluation of PARSAT took place for the winter academic semester 2022-2023 during the tutoring of the undergraduate course of “Technical Drawing” of a public University of the capital city of the country. In particular, three educators, and 240 undergraduate students, participated in the evaluation process. All the measurements of gender and age were derived from a randomly selected sample and do not have an impact on our research findings. The demographics analysis is shown in Table 4.

The population was equally divided by the instructors in two groups, each of which had equal number of students. The first group, namely experimental group, were asked to operate the PARSAT by themselves, taking advantage of the system’s adaptivity. For instance, the modeling of the students’ domain knowledge, offered them the opportunity to watch video tutorials of different duration, to rotate 3D objects of different complexity in order to visualize and understand their structures, and overall face different learning activities according to their personalized profile.

The second group, namely control group, used the learning material with the same learning activities, without any adaptivity in students’ personal profile. All three instructors were engaged in both groups.

Table 4. Demographics

Measure	Item	Frequency	Percentage (%)
Sample size		240	100.0
Gender	Male	151	62.9
	Female	88	36.7
	Non-binary	1	0.4
Age	15-17	0	0
	18-19	199	82.9
	Over 20	41	17.1
Prior knowledge	None	198	82.5
	High school course	42	17.5

After the completion of the course at the end of the semester, the two groups (experimental and control) were asked to answer a questionnaire, based on a 7-point Likert scale ranging from (1) strongly disagree to (7) strongly agree. The questions are the following [56], [57]:

Question 1 (Q1): The learning activities were in accordance with your knowledge level;

Question 1 (Q2): The number of the learning activities was effective;

Question 3 (Q3): PARSAT successfully identified your learning style.

Analyzing the answers to the aforementioned questions, we present the results in three pie charts (Figures 11-13).

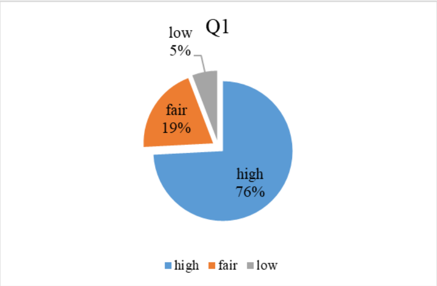


Fig. 11. Question 1 results

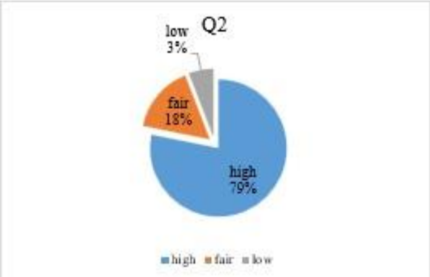


Fig. 12. Question 2 results

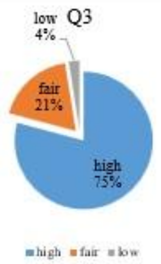


Fig. 13. Question 3 results

According to the evaluation results presented in the paper, a majority of the students found the learning activities to be appropriate for their knowledge level and effective for learning. Specifically, 182 students (76%) found the learning activities to be in accordance with their knowledge level, while 190 students (79%) found the number of learning activities to be appropriate for effective learning. Additionally, most students (180 or 75%) highly evaluated PARSAT as pedagogically useful for supporting their learning process. These positive evaluation results suggest that the proposed system, which utilizes fuzzy logic and AR technology, can provide a personalized and effective training experience for engineering students in the domain of technical drawing.

A statistical hypothesis test was used to assess the system more thoroughly. The 2-tailed *t*-test results indicate that there is a significant difference between the mean values of all three questions, which relate to the appropriateness of the learning activities, the number of learning activities, and the overall pedagogical usefulness of PARSAT. The *t*-Stat values for all three questions are greater than the critical *t* values, indicating that the results are statistically significant. This suggests that the proposed system, which incorporates an adaptive mechanism for learning activities, had a positive effect on student satisfaction and improved learning outcomes. Overall, the statistical analysis provides further evidence of the effectiveness of the PARSAT system for training engineering students in technical drawing.

Table 5. *t*-test results

	Question 1		**Question 2**		**Question 3**	
	Experimental group	Control group	Experimental Group	Control group	Experimental Group	Control group
Mean	6.03	3.71	6.48	3.66	6.01	3.29
Variance	0.74	0.43	0.42	0.49	0.57	0.65
t-Stat	2.72		4.04		3.79	
P two-tail	0.0016		0.00061		0.00035	
t Critical two-tail	2.01		1.89		1.97	

As far as the learning outcome is concerned, the authors compared the pretest-posttest results of an experimental group (120 students) who used the PARSAT system's adaptive learning material distribution using fuzzy logic, to a control group (also consisting of 120 students) who did not have access to this advanced functionality. All students, both in the experimental and control groups, took the same pretest to establish their prior knowledge of technical drawing. At the end of the semester, both groups took the same posttest, and a paired *t*-test was used to compare the differences in learning outcomes between the two groups. This approach allows the researchers to assess the effectiveness of the PARSAT system in improving learning outcomes in technical drawing.

Table 6 presents the evaluation results of the pretest and posttest scores of both the experimental and control groups. The experimental group had a pretest mean score of 4.19 and a posttest mean score of 6.24, indicating an improvement of 2.05 points. On the other hand, the control group had a pretest mean score of 4.38 and a posttest mean score of 5.01, indicating an improvement of only 0.63 points. While both groups improved their scores, the improvement in the experimental group was significantly greater than that of the control group, indicating that the adaptive system used by the experimental group had a positive impact on their learning outcomes.

Table 6. *t*-test results of the pretest and the posttest scores

	Experimental group	**Control group**
Pretest Mean	4.19	4.38
Posttest Mean	6.24	5.01
Difference	2.05	0.63
t-Stat	4.23	1.64
P-value	0.00033	0.0038

The evaluation results presented in Table 6 show the pretest and posttest mean scores of the experimental and control groups. A pretest is a test administered before the instruction, while a posttest is a test administered after the instruction. By comparing the pretest and posttest scores, the authors determined how much the instruction has improved students' learning outcomes.

In this study, the experimental group used the PARSAT system, which provided adaptive learning material distribution using fuzzy logic, while the control group did not have access to this system. The results show that both groups improved their scores from the pretest to the posttest. However, the experimental group showed a much greater improvement than the control group, indicating that the adaptive system used by the experimental group had a positive impact on their learning outcomes.

7. Conclusion

This paper presents PARSAT, which is a mobile augmented reality application for the training of spatial skills. PARSAT asks the user to insert three inputs, namely age, gender and prior knowledge, and personalizes the educational experience to each student. The adaptivity is accomplished by employing fuzzy weight-based decisions, defining the students’ domain knowledge level, and according to the fuzzy logic results, each student receives different learning activities.

The findings of the system's evaluation are quite encouraging, as they show a high level of student satisfaction and improved learning outcomes. Students gave this personalized teaching approach a high feedback grade, indicating the correctness of the learning activities supplied, depending on their knowledge level. Finally, the pretest and posttest evaluations revealed a considerable improvement in students' scores, verifying the pedagogical suitability of the proposed learning approach.

In addition to the findings, there are some limitations related to screen size, hardware variability, and the limited computational resources of mobile devices. This can result in slower performance and limitations in the types of augmented reality experiences that can be created.

The current research focuses on providing students with appropriate learning activities based on their knowledge level as the primary determinant of their adaptability. Incorporation of extra fuzzy weights regarding other students' characteristics, such as emotional state and/or types of mistakes is a future inquiry coming from this work, with the goal of improving system adaptation, and, hence learning outcomes.

Integrating hybrid algorithmic techniques for modelling student knowledge can be a promising future extension. By combining different techniques, such as fuzzy logic, Bayesian networks, and decision trees, it may be possible to create more accurate and reliable student models. This can lead to more personalized and effective learning experiences for individual learners.

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