

# Personalized Learner Assistance through Dynamic Adaptation of Chatbot using Fuzzy Logic Knowledge Modeling

Christos Troussas, Akrivi Krouska, Phivos Mylonas, Cleo Sgouropoulou

Department of Informatics and Computer Engineering

University of West Attica

Egaleo, Greece

{ctrouss, akrouska, mylonaf, csgouro}@uniwa.gr

**Abstract**—Personalized approaches and tailored support have become increasingly significant in the field of online education, aiming to enhance the overall learning experiences of learners. This paper introduces a novel approach for addressing challenges in providing tailored support by utilizing chatbot technology and the flexibility of fuzzy logic. The chatbot is responsible for delivering precise and tailored responses to learners, considering their input, typically in text form. This is accomplished through the utilization of a rule-based system that is capable of generating accurate answers according to predefined criteria. To augment this support, fuzzy logic is employed for modeling the learners' knowledge, thereby enhancing the chatbot's proficiency in accurately evaluating and responding to inquiries. Consequently, the provision of assistance can be tailored to the specific knowledge level of learners, aiding them in achieving their educational goals. This methodology is incorporated in an intelligent tutoring system designed to provide tutoring for the programming language Java. The evaluation findings demonstrated the effectiveness of our approach in delivering personalized assistance through a chatbot. The results indicated that the chatbot's responses were highly rated in terms of clarity, relevance, and usefulness. Additionally, the system was found to effectively address learners' needs with quality and adequacy.

**Keywords**—*intelligent tutoring systems; intelligent agents; personalized assistance; distance learning; chatbot; fuzzy logic; rule-based system.*

## I. INTRODUCTION

In the realm of e-learning, personalized strategies and individualized assistance have gained considerable importance as effective strategies for enhancing learners' educational experiences [1,2]. Learners can greatly benefit from tailored support that caters to their specific needs and preferences. One effective approach to achieving personalized assistance is through the utilization of chatbots, which offer real-time guidance and support [3].

Chatbots have emerged as promising tools for delivering personalized support in education due to their accessibility, responsiveness, and adaptability. However, challenges exist in accurately understanding learner queries, generating appropriate responses, and adapting to changing learning

contexts [4]. Engaging learners and maintaining motivation throughout the learning process are also critical for the success of chatbot-based assistance.

To ensure personalized assistance, it is essential to take into account the unique characteristics of learners, including their knowledge level. Various intelligent techniques have been employed to model learners' knowledge, enabling a deeper understanding of their individual capabilities and needs. One prevalent technique in this regard is fuzzy logic, which has been widely utilized in numerous systems [5]. Fuzzy logic proves valuable in this context due to its ability to represent and analyze uncertain and imprecise information effectively. By leveraging the power of fuzzy logic, systems can capture the nuanced nature of learners' knowledge, leading to more accurate and tailored support in educational settings [5,6].

Analyzing the related literature, there has been substantial research conducted on the topic of chatbots in educational settings and the utilization of fuzzy logic for modeling learners' knowledge. The integration of chatbots in education has gained significant attention due to their potential to provide personalized and adaptive learning experiences. These intelligent conversational agents have been explored as tools for delivering educational content [7-9], facilitating learner engagement [10-12], offering personalized assistance [13-15], evaluating learners' knowledge [16-18]. Also, fuzzy logic has emerged as a powerful approach for modeling learners' knowledge, particularly due to its ability to handle uncertainty and imprecision inherent in educational contexts. Researchers have investigated the effectiveness of fuzzy logic in capturing the complex and dynamic nature of learners' knowledge, allowing for more accurate assessments, personalized recommendations, and targeted interventions [19-24].

In view of the above, this paper presents a novel approach for personalized learner assistance through the dynamic adaptation of a chatbot using fuzzy logic knowledge modeling. The paper aims to address the challenges in providing tailored support and assistance to learners by leveraging the capabilities of chatbot technology and the flexibility of fuzzy logic. The proposed framework incorporates a two-layer rule-based system that allows the chatbot to deliver adequate responses. By considering learners' knowledge level, the chatbot can

provide customized explanations, examples and resources that align with the learner's specific needs through the use of fuzzy logic. The utilization of fuzzy logic enables the modeling of uncertain cases, enhancing the chatbot's ability to accurately assess and respond to learners' queries and requests. This approach has been incorporated in an intelligent tutoring system for learning the programming language Java. The subject matter encompasses introductory as well as advanced concepts in Java programming.

## II. LEARNERS' KNOWLEDGE MODELING USING FUZZY LOGIC

The provision of student assistance necessitates the consideration of their knowledge level, which, in itself, is not a straightforward task and is accompanied by uncertainty. For example, a student with a score of 7/10 cannot be definitively classified as either good or very good, as both classifications hold a certain degree of truth. To address this issue, fuzzy logic emerges as a viable solution. Within this framework, three fuzzy weights, namely Novice (N), Intermediate (I), and Expert (E), have been defined to denote the knowledge level of students in learning the Java programming language. Each fuzzy weight is represented by trapezoidal membership functions, characterized by four boundary values ( $a_1, a_2, a_3, a_4$ ). The membership degree increases from 0 to 1 between  $a_1$  and  $a_2$ , remains at 1 between  $a_2$  and  $a_3$ , and then decreases from 1 to 0 between  $a_3$  and  $a_4$ . The selection of trapezoidal membership functions stems from the fact that within each knowledge level category, there exists an interval (between  $a_2$  and  $a_3$ ) where students' scores fully align with the corresponding category.

TABLE I. FUZZY WEIGHTS.

Knowledge Level	
Membership Function	Interval
Novice (N)	
$\mu_N(x) = \begin{cases} 1 & x \leq 3 \\ 1 - \frac{x-3}{2} & 3 < x < 5 \\ 0 & x \geq 5 \end{cases}$	(0, 0, 3, 5)
Intermediate (I)	
$\mu_I(x) = \begin{cases} \frac{x-3}{2} & 3 < x < 5 \\ 1 & 5 \leq x \leq 7 \\ 1 - \frac{x-7}{1} & 7 < x < 8 \\ 0 & x < 3 \text{ or } x \geq 8 \end{cases}$	(3, 5, 7, 8)
Expert (E)	
$\mu_E(x) = \begin{cases} \frac{x-7}{1} & 7 < x < 8 \\ 1 & 8 \leq x \leq 10 \\ 0 & x \geq 10 \end{cases}$	(7, 8, 10, 10)

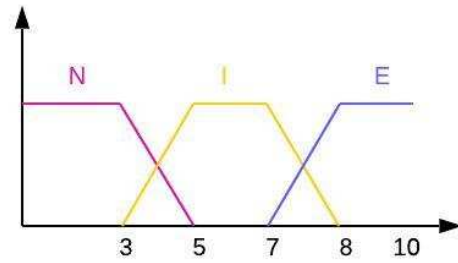


Fig. 1. Fuzzy weights.

Based on the aforementioned considerations, the three fuzzy weights have been employed to represent the current knowledge level of students in the specific domain of Java programming. These fuzzy weights are assigned values ranging from 0 to 1, with a value of 1 indicating complete mastery and familiarity with the domain. Consequently, the cumulative value of the divided fuzzy sets represents the knowledge level of a learner in the domain, and the equation  $\mu_N(x) + \mu_I(x) + \mu_E(x) = 1$  holds true.

To establish the fuzzy weights and determine the thresholds for their membership functions, a group of 15 faculty members specializing in computer programming tutoring from public universities participated in the process. These experienced faculty members, with over 10 years of experience in teaching programming languages at the university level, provided descriptive definitions of learners' knowledge levels in the context of learning Java. They also specified the success thresholds corresponding to each knowledge level. By leveraging their expertise, the faculty members ensured an accurate portrayal of students' knowledge levels, thereby minimizing any potential errors.

## III. DYNAMIC ADAPTATION OF CHATBOT

The chatbot is responsible for providing specific and accurate answer to learners based on their input, which can be in text format. This is achieved using a rule-based system that is able to provide accurate responses based on predefined criteria. The rule-based system of the chatbot employs a two-layer approach. The first layer consists of generic rules, while the second layer consists of rules that are tailored to each category of learners.

The general rule set serves as the starting filter for all learner types at the first layer. These rules are made to accommodate various types of inquiries and to deal with frequent ones. For instance, it contains rules that address factual issues, seek for clarity on ideas, offer instances or illustrations, and provide more resources or material. These guidelines form the chatbot's knowledge base and give it the flexibility to respond to a variety of learner queries, as shown in the following rules:

- Rule 1:
  - Condition: If a factual question is posed by the learner.

- Action: If the query includes the terms “What”, “Who”, or “When”, give a brief and factual response from the knowledge source.
- Rule 2:
  - Condition: If a learner wants further information on a concept.
  - Action: If the query contains terms that indicate misunderstanding or confusion, give a brief clarification or more examples to help the reader comprehend.
- Rule 3:
  - Condition: If the learner requests examples or illustrations.
  - Action: If the query contains keywords like “Example” or “Illustration”, provide relevant examples or visual aids to enhance understanding.
- Rule 4:
  - Condition: If a learner indicates that they favor a particular learning style
  - Action: If a learner says that s/he is a visual learner, include diagrams, charts, or pictures to illustrate the points.
  - Action: Break down complex concepts into logical steps if the learner is more comfortable with step-by-step instructions.
- Rule 5:
  - Condition: If the learner requests further sources or references
  - Action: If a query includes terms like “Reference” or “Further Reading”, give some suggested resources, such as books, articles or online materials.

The chatbot contains more precise rules that are adapted to each learner category (novice, intermediate, and expert) in the second layer. These guidelines consider the diverse degrees of knowledge and expertise displayed by students in several areas. For instance, rules tailored to beginners are intended to cover core ideas, offer clearer explanations, and provide step-by-step guidance for simple programming jobs. Intermediate-specific rules concentrate on increasingly complex linguistic elements, industry standards, and problem-solving techniques that are pertinent to learners in that group. The advanced themes, optimization strategies, and project-related queries that are specific to learners with a greater level of experience are covered by expert-specific rules. The second layer of predefined rules encompasses different approaches based on the proficiency levels of learners.

For Novice learners, the chatbot focuses on simplifying explanations, providing step-by-step guidance, and offering basic examples. It aims to use clear language, avoid complex

technical terms, break down tasks into manageable steps, and emphasize fundamental concepts.

Intermediate learners receive assistance that builds upon their foundational knowledge. The chatbot acknowledges their existing understanding and introduces more advanced concepts, techniques, and best practices. It also provides suggestions for code optimization, efficient coding patterns, and debugging strategies to enhance their skills.

Expert learners engage in discussions about advanced topics, including cutting-edge techniques, emerging trends, and critical analysis. The chatbot encourages them to think critically, explore new ideas, and stay updated with the latest advancements in the field. Additionally, it assists them in finding and comprehending research papers, academic resources, and industry-specific case studies.

Given the aforementioned considerations, in situations where both novice and expert users pose the same question, the chatbot demonstrates its ability to adapt its response based on the learner's category. This adaptive feature enables the chatbot to tailor its answer to suit the specific knowledge level and requirements of each learner. For example, let's assume that a novice and an expert user types “Tell me how I can iterate over an array.” The chatbot will give the following responses:

- To the novice learner: “You can iterate over an array using for loop.”, followed by the corresponding code in Java.
- To the expert learner: “Depending on your objectives and coding preferences, there are several techniques you can investigate when it comes to iterating over an array in Java. In addition to the conventional for loop and for-each loop, you might also take into account more sophisticated strategies like utilizing the Iterator interface or Java 8's Stream API for more functional programming techniques. To improve your comprehension of array iteration in Java, it is advised that you investigate these ideas in more detail.”, followed by the corresponding code in Java.

#### IV. EVALUATION

The evaluation was carried out within the informatics conversion course at a public university located in the capital city, within the authors' department. The sample for the evaluation comprised 70 postgraduate students who were enrolled in the mandatory Java programming course. All the students belonged to the first year of studies and had similar age and educational backgrounds. The evaluation process spanned an entire semester. It is worth noting that the course was conducted online and synchronously, and the students relied on the system throughout this period to support their learning. The students displayed a high level of interest in using the system and received support from lecturers whenever required.

To ensure a rigorous evaluation process, the lecturers divided the students into two equally sized groups (Groups A and B), with 35 students in each group. The division of students into groups was carried out meticulously by the

lecturers, taking into consideration their individual characteristics in order to maintain the quality of the evaluation. During the initial evaluation phase, all students from Groups A and B were provided with a questionnaire at the end of the academic semester to assess the system. The questionnaire consisted of five questions that evaluated different dimensions, as presented in Table II.

TABLE II. QUESTIONS

Dimension (D)	Question (Q)	Scale
Clarity of Responses (D1)	Rate the clarity of the explanations provided by the chatbot. (Q1)	1 (lower) to 5 (higher)
Relevance of Responses (D2)	Rate the relevance of the chatbot's responses to your needs. (Q2)	
Usefulness of Responses (D3)	Rate the usefulness of the chatbot's responses to your learning needs. (Q3)	
Personalized Assistance (D4)	To what extent did the chatbot provide personalized assistance tailored to your individual needs? (Q4)	
Adequacy of Addressing Individual Needs (D5)	Were your specific questions or concerns resolved satisfactorily by the chatbot? (Q5)	

Regarding D1 (Fig. 2), the students' responses exhibit a significantly high rating, indicating a strong positive experience regarding the clarity of the explanations provided. Moreover, when analyzing D2, the students' assessments highlight a substantial correlation between the chatbot's responses and their specific needs, demonstrating a high level of relevance. In terms of D3, the students' feedback emphasizes the substantial utility of the chatbot's responses in addressing their individual learning needs. Moving on to D4, the students report a statistically significant level of personalized assistance provided by the chatbot, specifically tailored to their unique requirements. Finally, when evaluating D5, the students affirm that their specific questions and concerns were resolved satisfactorily by the chatbot, with a high level of confidence. These findings provide strong statistical evidence to support the conclusion that the chatbot consistently performs at a high level across all evaluated dimensions, thereby significantly enhancing the students' overall learning experience.

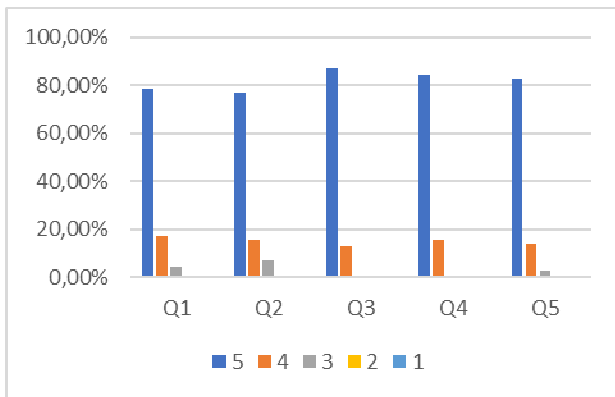


Fig. 2. Learners' responses.

To further investigate the impact of the presented system on students regarding the Usefulness of Chatbot's Responses and Personalized Assistance, a statistical hypothesis test (t-test) was conducted. The test compared the performance of the presented system (Group A) with its conventional version (Group B). The conventional version of the chatbot shared the same interface and utilized the same rule-based approach, lacking the incorporation of fuzzy logic for personalized learner assistance. The t-test was specifically applied to questions Q3 and Q4, which focused on assessing these aspects (Table III).

TABLE III. T-TEST RESULTS.

	Q3		Q4	
	Group A	Group B	Group A	Group B
Mean	4,742 857	2,54285 7	4,68571 4	2 2
Variance	0,196 639	0,25546 2	0,22184 9	0,35294 1
Observations	35	35	35	35
Pooled Variance	0,226 05		0,28739 5	
Hypothesized Mean Difference	0		0	
df	68		68	
t Stat	19,35 704		20,9574 9	
P(T<=t) one-tail	1,14E- 29		1,1E-31	
P(T<=t) two-tail	2,27E- 29		2,2E-31	

Based on the aforementioned findings, it can be deduced that there is a statistically significant distinction between the means of the two groups regarding Q3 and Q4. Specifically, it was observed that our software, utilized by Group A, exhibited substantial performance concerning the usefulness of the chatbot's responses to students' learning needs compared to the conventional version used by Group B (Q3:  $t \text{ Stat} \approx 19,3$ ,  $p < 0,05$ ). Moreover, there was a significant difference in the personalization of chatbot's assistance tailored to students' individual needs between Group A (Mean  $\approx 4,68$ , Variance  $\approx 0,22$ ) and Group B (Mean = 2, Variance  $\approx 0,35$ ), where  $t \text{ Stat} \approx 12,18$ ,  $p \approx 2,47 \times 10^{-21}$ .

## V. CONCLUSIONS

In this paper, we explored the application of personalized learner assistance through dynamic adaptation of a chatbot using fuzzy logic knowledge modeling. The system utilizes fuzzy logic knowledge modeling to provide tailored recommendations and assistance to learners through the chatbot using a rule-based approach. Our findings demonstrate that the incorporation of fuzzy logic knowledge modeling in the chatbot system leads to positive results in terms of learner assistance.

In our future research, we plan to incorporate machine learning techniques into the chatbot system. This integration

will enable us to explore how such algorithms can enhance the system's adaptability and overall performance.

## REFERENCES

- [1] B. Levy, A. Hershkovitz, M. Tabach, A. Cohen, A. Segal and K. Gal, "Personalization in Graphically Rich E-Learning Environments for K-6 Mathematics," in *IEEE Transactions on Learning Technologies*, vol. 16, no. 3, pp. 364-376, 1 June 2023, doi: 10.1109/TLT.2023.3263520.
- [2] C. Troussas, K. Chrysafiadi, M. Virvou, "Machine Learning and Fuzzy Logic Techniques for Personalized Tutoring of Foreign Languages", in: *Artificial Intelligence in Education. AIED 2018*, vol. 10948, Carolyn Penstein Rosé, et al. Eds. Lecture Notes in Computer Science(), Springer, Cham, 2018, pp. 358-362, doi: 10.1007/978-3-319-93846-2\_67.
- [3] E. Kasthuri and S. Balaji, "A Chatbot for Changing Lifestyle in Education," 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV), Tirunelveli, India, 2021, pp. 1317-1322, doi: 10.1109/ICICV50876.2021.9388633.
- [4] M.A. Kuhail, N. Alturki, S. Alramlawi, et al., "Interacting with educational chatbots: A systematic review", *Educ Inf Technol*, vol. 28, pp. 973-1018, 2023, doi:10.1007/s10639-022-11177-3.
- [5] A. Krouska, C. Troussas, and C. Sgouropoulou, "Fuzzy Logic for Refining the Evaluation of Learners' Performance in Online Engineering Education", *EJENG*, vol. 4, no. 6, pp. 50-56, Jun. 2019, doi: 10.24018/ejeng.2019.4.6.1369.
- [6] S. Wen and D. Liu, "Students' Learning Performance Evaluation Using a New Fuzzy Inference System," 2021 2nd International Conference on Artificial Intelligence and Education (ICAIE), Dali, China, 2021, pp. 650-656, doi: 10.1109/ICAIE53562.2021.00143.
- [7] C. Troussas, A., Krouska, M. Virvou, "MACE: Mobile artificial conversational entity for adapting domain knowledge and generating personalized advice", *International Journal on Artificial Intelligence Tools*, vol. 28, no. 04, 1940005, 2019, doi: 10.1142/S0218213019400050.
- [8] H. Steinbeck, T. E. I. Zobel and C. Meinel, "Towards leveraging conversational agents for instructors and learners to find and access learning resources," 2021 World Engineering Education Forum/Global Engineering Deans Council (WEEF/GEDC), Madrid, Spain, 2021, pp. 607-611, doi: 10.1109/WEEF/GEDC53299.2021.9657307.
- [9] B. Shivashankar, A. M. A. Sundari, H. Surendra, S. S. Atul Sai and M. Moharir, "Deep Learning based Campus Assistive Chatbot," 2021 IEEE International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS), Bangalore, India, 2021, pp. 1-4, doi: 10.1109/CSITSS54238.2021.9683551.
- [10] N. A. Nasharuddin et al., "Designing an Educational Chatbot: A Case Study of CikguAIBot," 2021 Fifth International Conference on Information Retrieval and Knowledge Management (CAMP), Kuala Lumpur, Malaysia, 2021, pp. 19-24, doi: 10.1109/CAMP51653.2021.9498011.
- [11] Y. -H. Lin and T. Tsai, "A Conversational Assistant on Mobile Devices for Primitive Learners of Computer Programming," 2019 IEEE International Conference on Engineering, Technology and Education (TALE), Yogyakarta, Indonesia, 2019, pp. 1-4, doi: 10.1109/TALE48000.2019.9226015.
- [12] D. E. Gonda and B. Chu, "Chatbot as a learning resource? Creating conversational bots as a supplement for teaching assistant training course," 2019 IEEE International Conference on Engineering, Technology and Education (TALE), Yogyakarta, Indonesia, 2019, pp. 1-5, doi: 10.1109/TALE48000.2019.9225974.
- [13] S. Amarnani, N. Bhagat, H. Ekade, A. Gupta and S. Sahu, "A Complete Chatbot based Architecture for answering user's Course-related queries in MOOC platforms," 2021 International Conference on Computing, Communication and Green Engineering (CCGE), Pune, India, 2021, pp. 1-7, doi: 10.1109/CCGE50943.2021.9776437.
- [14] D. Song, E. Y. Oh and M. Rice, "Interacting with a conversational agent system for educational purposes in online courses," 2017 10th International Conference on Human System Interactions (HSI), Ulsan, Korea (South), 2017, pp. 78-82, doi: 10.1109/HSI.2017.8005002.
- [15] R. Ramjattan, P. Hosein and N. Henry, "Using Chatbot Technologies to Help Individuals Make Sound Personalized Financial Decisions," 2021 IEEE International Humanitarian Technology Conference (IHTC), United Kingdom, 2021, pp. 1-4, doi: 10.1109/IHTC53077.2021.9698928.
- [16] C. Troussas, A. Krouska and M. Virvou, "Integrating an Adjusted Conversational Agent into a Mobile-Assisted Language Learning Application," 2017 IEEE 29th International Conference on Tools with Artificial Intelligence (ICTAI), Boston, MA, USA, 2017, pp. 1153-1157, doi: 10.1109/ICTAI.2017.00176.
- [17] S. H. Afrizal, N. Hakiem, A. Erna Permanasari, H. Syaifullah Albab, G. Yoki Sanjaya and L. Lazuardi, "A User-Centered Design of Natural Language Processing for Maternal Monitoring Chatbot System," 2022 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS), Jakarta, Indonesia, 2022, pp. 244-248, doi: 10.1109/ICIMCIS56303.2022.10017517.
- [18] V. Jathushan, B. Senthujan, B. Ajiharan, M. Kasthury, A. Gamage and D. Ganegoda, "Smart Teacher - An AI-Based Self-Learning Platform for Grade 10 ICT Students," 2022 IEEE 7th International conference for Convergence in Technology (I2CT), Mumbai, India, 2022, pp. 1-5, doi: 10.1109/I2CT54291.2022.9824753.
- [19] K. Chrysafiadi, C. Troussas, M. Virvou, "Combination of fuzzy and cognitive theories for adaptive e-assessment", *Expert Systems with Applications*, vol. 161, 2020, 113614, doi: 10.1016/j.eswa.2020.113614.
- [20] C. Papakostas, C. Troussas, A. Krouska, and C. Sgouropoulou, "Personalization of the Learning Path within an Augmented Reality Spatial Ability Training Application Based on Fuzzy Weights," *Sensors*, vol. 22, no. 18, p. 7059, Sep. 2022, doi: 10.3390/s22187059.
- [21] M. S. Ivanova, "Fuzzy Set Theory and Fuzzy Logic for Activities Automation in Engineering Education," 2019 IEEE XXVIII International Scientific Conference Electronics (ET), Sozopol, Bulgaria, 2019, pp. 1-4, doi: 10.1109/ET.2019.8878622.
- [22] K. Almohammadi, B. Yao, A. Alzahrani, H. Hagra and D. Alghazzawi, "An interval type-2 fuzzy logic based system for improved instruction within intelligent e-learning platforms," 2015 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Istanbul, Turkey, 2015, pp. 1-9, doi: 10.1109/FUZZ-IEEE.2015.7338050.
- [23] J. Bohacik and M. Zabovsky, "Fuzzy Rule Miner: A Software Library Used in Project Based Teaching of Topics Related to Knowledge Discovery in Databases," 2018 16th International Conference on Emerging eLearning Technologies and Applications (ICETA), Stary Smokovec, Slovakia, 2018, pp. 75-80, doi: 10.1109/ICETA.2018.8572093.
- [24] R. K. Grace, S. Manju, M. S. G. Devasena and V. K. Kumar, "Student competency analysis: An automated robust tool using fuzzy logic," 2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), Coimbatore, India, 2017, pp. 1-5, doi: 10.1109/ICIIECS.2017.8275840.