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Analysis and Design of Fuzzy Logic based Adaptive E-Learning and Evaluation Framework

Santosh Kumar[1], Baldev Singh[2], Madan Mohan Agarwal[3]
Research Scholar, Vivekanad Global University, Jaipur, India[1]
Professor, Computer Science & Engineering, Vivekanad Global University, Jaipur, India[2]
Assistante Professor, Computer Science & Engineering, Birla Institue of Technology Mesra, India[3]
ska.bitjpr@gmail.com[1], baldev_singh@vgu.ac.in[2], mmagarwal@bitmesra.ac.in[3]

ABSTRACT
Early e-learning systems primarily followed a "one size fits all" approach, offering uniform course content to all learners, irrespective of their individual learning styles or needs. Over time, this model has evolved significantly with the advent of rapid e-learning tools that integrate features such as online video, audio, and desktop recording—all within a single platform. These tools allow instructional designers to build engaging and interactive content using simple drag-and-drop and overlay elements. Research shows that students often learn more effectively from digital materials than from traditional printed lectures. The widespread use of smart devices, laptops, and computers in higher education has simplified the creation and delivery of digital learning content. This shift has also influenced learning preferences, driving the demand for more personalized, adaptive, and intelligent educational systems. Recent studies have emphasized the development of knowledge-based models that adapt to individual learners. This design provides better results and evaluation of existing e-learning systems, their limitations, and the design of adaptive intelligent frameworks using fuzzy logic to enhance learning and assessment processes.

KEYWORDS: Adaptive learning, intelligent e-learning, evaluation, parameters, fuzzy logic.

1. INTRODUCTION

The literature review involves examining the existing e-learning system to assess its current state and compare it with a framework for adaptive intelligent learning and evaluation aimed at enhancing the e-learning experience. E-learning represents a significant application of Information Technology, and considerable research has been dedicated to developing effective e-learning systems. In my research, I focus on reviewing the literature related to a framework for adaptive learning and evaluation to improve e-learning, which aims to enhance the knowledge of students and other learners.

Numerous e-learning platforms fail to address the diverse needs and abilities of their students by offering uniform materials. Students have a wide range of needs, goals, backgrounds, and educational skills. These diverse characteristics overlooked by current e-learning systems, prompting development a framework for adaptive intelligent learning assessments and improved e-learning experiences. This framework is designed to tailor its features and interfaces to meet the varying needs of users. An adaptive intelligent learning and evaluation framework aims to address the challenges faced by current e-learning systems. It modifies the way information is presented to align with the unique needs and preferences of each student and assesses their performance.

2. LITERATURE REVIEW

Early e-learning systems were designed around Computerized Learning or Training, focusing on authoritative knowledge delivery. This shifted with the rise of Computer-Supported Collaborative Learning (CSCL), which emphasizes shared knowledge construction. Learning Management Systems (LMSs) have become central to e-learning, offering integrated tools for learning, communication, and collaboration. However, most LMSs follow a "one size fits all" model, lacking personalized support for learners with diverse needs and goals. Similarly, many Advanced Web-Based Educational Systems (AWBES), such as SCORM, DALMOOS, Net-Coach, and SIETTE, deliver identical content to all users. Although functional, these systems often overlook the evolving, individualized requirements of both students and educators.

Adaptive web-based educational systems offer a personalized alternative to traditional "one-size-fits-all" courseware by tailoring content based on each student's goals, knowledge, and preferences. These systems often use adaptive hypermedia technologies, considering factors such as prior knowledge, interests, and learning backgrounds [1]. However, teaching strategies remain to be explored. A fuzzy clustering approach has been used to build student models from web activity, although many systems lack published qualitative evaluations of their educational effectiveness [2].

Conventional e-Learning systems often ignore individual learner differences and offer uniform content to all [3]. Adaptive learning, powered by AI and data-driven approaches, personalizes content based on students' traits, behaviour, and educational background. Smart classrooms use AI technologies for intelligent content delivery, real-time evaluations, and personalized feedback. These environments enhance engagement and performance through the use of interactive tools, mobile access, and adaptive systems [4]. This research highlights opportunities for further development of smart learning technologies and classroom optimization.

In 2022, [5] conducted a survey on the use of artificial intelligence in smart classrooms. Building on this, this report offers a deeper analysis of smart classroom technologies and examines both the benefits and limitations of AI in education. AI has enhanced e-learning through Adaptive Learning Systems, which personalize instruction based on individual student profiles, including goals, traits, and learning styles [6]. These systems dynamically adapt to content and teaching methods. Recently, an open-source platform, 'Edu4AI', was developed to customize curricula according to each student's skills, learning style, and academic progress, offering a highly personalized educational experience [7].

Research [8] explored the growing role of AI in education, emphasizing its applications in software, humanoid robots, chatbots, and online platforms. The survey also analyzed the number of research groups in each area and the most common AI-related terms in the academic literature. Smart classrooms aim to enrich the teaching and learning experiences by integrating advanced technologies. Teachers are expected to enhance student performance and creativity through social, mobile, and universal learning approaches while balancing technical tools and effective pedagogical strategies [9].

These methods enhance course quality and shorten the time required for development by providing pertinent educational materials. Nonetheless, a significant challenge is the mistaken belief that learning objects are simple files that can be stored and reused. They consist of dynamic web-based activities managed by servers, necessitating appropriate hosting and integration, particularly in adaptive online learning settings that utilize reusable learning objects.

A key issue in online learning is the limited flexibility in accessing and selecting course content. Static resource integration and uniform content structures can hinder personalized learning, preventing students from fully utilizing updated resources and meeting diverse learning needs in courses shared by large and varied student groups.

2.1. ADAPTIVE SYSTEMS BASED ON LEARNING STYLES

To ensure flexibility and effectiveness in online learning platforms, it is crucial for systems to integrate adaptive learning and teaching strategies. Several educational hypermedia systems have been developed to accommodate various learning styles [10–11]. These systems are expected to be evaluated and classified based on their targeted learning styles. The Adaptive Educational System based on Cognitive Styles (AES-CS) [12] is a prominent framework similar to the Felder-Silverman global-sequential dimension used in the Learning Styles Adaptive System (LSAS) [13] and CS388 [14]. Field-dependent learners typically prefer a global learning approach, rely on existing structures, focus on relevant content, and align their goals with personal experiences. They value organization, respond strongly to feedback, and understand concepts via observation.

Adaptive hypermedia systems enhance learning by offering navigation aids, such as concept maps, visual path indicators, and dynamic organizers, that help predict the structure of knowledge domains. AHA systems provide learner-controlled flexibility and adaptive presentations of content, such as text, audio, video, animations, simulations, puzzles, and hypermedia. Alternative learning approaches, such as the intuitive-sensing dimension scale proposed by Felder and Silverman [18], have been implemented in systems such as Tangow [19]. Instinctive learners prefer structured problem-solving, whereas intuitive learners thrive on discovery and abstract concepts.

Adaptive navigational support methods, such as hyperlink annotation, are used by Adaptive Hypermedia (AH) systems to accommodate diverse learning styles by recommending various information sequences to learners. One notable example is the Adaptive Hypermedia Architecture (AHA!) [20], which guides learners by conditionally hiding links or offering additional explanations in online learning environments. In contrast, systems such as Interbook [15] and KBS-Hyperbook [16] focus on structural integrity and often rely on psychometric questionnaires to classify users into stereotypical learning groups. These classifications are typically static and cannot be revised during the learning process of the model. However, the AHA! The system addresses this limitation by providing tools for creating dynamic, personalized strategies that adapt throughout the learning journey. Unlike earlier models, our proposed method allows flexibility in developing multiple adaptive approaches for various learning styles without any predefined constraints. Table 1 presents comparative analysis of existing adaptive learning systems, their methodologies, and the advantages of our proposed learning style–oriented framework.

Table1: The learning styles incorporated into the adaptive systems

Adaptive System	Learning Style
weaver [13]	Auditory, manual, kinaesthetic, impulsive, reflective, global, analytical styles of Dunn and Dunn learning style model [24]
ARTHER [8]	Visual-interactive, auditory-lecture and text styles
CS388 [14]	Felder Silverman learning styles model [18]. Global-sequential, visual-verbal, sensing-intuitive, inductive-deductive styles
AES-CS [12]	Field-dependent (FD) and Field –independent style
LSAS [13]	Global sequential dimension of the Felder Silverman learning style model
MANIC [17]	Applies preferences for graphic versus textual information
INSPIRE [15]	Categorization of activists, pragmatists, reflectors and theorists based on Kolb
TANGOW [19]	Sensing-intuitive dimension from the Felder Silverman learning style model
AHA![16]	Does not provide any questionnaires for assessing learning styles. (Adaptive Hypermedia Architecture)
3DE [23]	Honey and Mumford [25] categorization of activists, pragmatists, reflectors and theorists based Kolb [22]
AACWELS	Felder's questionnaires [26] form after modified it depending on the properties of each style according to Honey and Mumford [25]

2.2. ADAPTIVE E-LEARNING SYSTEMS AND COURSE CONTENT HANDLING

The Adaptive Hypermedia Architecture (AHA) provides open-access frameworks for developing adaptive web-based courses. The AHA adjusts hyperlink structures by removing, hiding, or annotating links to generate personalized content. Using CGI scripts and HTML preprocessors, the AHA filters and adapts the content and links based on user input. While some systems assume that all users share a similar background. Several adaptive hypermedia systems, such as ELM, ARTERPT, INTERBOOK, and AHA, incorporate similar adaptation elements.

Table 2: Comparisons with the existing adaptive systems and the proposed system

Adaptive System	Adaptive Sequencing	Adaptive Navigation	Adaptive Presentation	Adaptive learning Material
ELM-ART	Page	Anotation	Some	Same level
ELM-ART-II	Course tests	Anotation	Some	Same level
Inter Book	Page	Anotation	Some	Same level
AHA	Not exist	Annotation, Hiding	Yes	Same level
SHETTE	Question	Not exist	Not exist	Same level
ILESA	Lesson, problem	Server, java	Not exist	Same level
AACWELS	Course test	Annotation, Hiding	Yes	Same level
AILEF	Lession, problem, quiz, test	Anotation, Hiding	Yes	Different level of learning material

The adaptive notation in Table 2 means that the system uses visual indicators, that is, icons, fonts, and color, to indicate types and levels of education for each link. A comparison of the adaptation methods applied to these systems is shown in Table 3.

Table 3: A Comparison between various adaptation techniques

Adaptation Techniques	AHA	KBS	ELM-ART	AACWELS	AILEF
Learning contents	Yes	Yes	Yes	Yes	Yes
Pedagogical devices	No	Yes	Yes	Yes	Yes
Communication support	No	No	Yes	Yes	Yes
Problem-solving support	No	No	Yes	Yes	Yes
Assessment	No	No	Yes	Yes	Yes
Level of learning content	No	No	No	No	Yes

An online intelligent learning platform was developed to assist educators in designing simple algorithms for teaching. It focuses on algorithmic learning and problem-solving, especially in exercise-based training, such as ILESA. The system includes subsystems such as an expert system for Linear Programming, a Problem Exporter, Student Model, Diagnostic System, and an engine. ILESA offers an active support system and a web interface that adapts problems to each student's knowledge level, assessing responses to guide learning [23]. With the rise of accessible and accurate information online, e-learning has become a highly effective educational tool for both students and educators [27].

A study examining the impact of e-learning on student engagement found that students who participated were more engaged with the training materials and had higher pass rates than those who did not. This suggests that e-learning may represent the future of education [28]. Another study demonstrated that the number of learners accessing and completing e-learning courses was encouraging [29]. Research by [30] and [31] indicated that traditional teaching methods are not very engaging for students today, and ' 'computer-mediated communication ' (CMC) has become an essential and crucial tool in education.

Researchers explain that multimedia involves the integration of various media types, including audio, video, images, text, and animations, to deliver information to users through a 'computerized format.' One example of software used to develop interactive multimedia programs is "Adobe Flash" [32]. In 2015, Chachil researched interactive multimedia and created a 'mobile-based app' for learning the Iban language. Software based on interactive multimedia is highly beneficial for education because it simplifies the learning process

[33]. Kim et al. (2013) discussed how interactive multimedia enhances education by addressing students' emotional needs, thereby making learning more effective. Digital platforms that utilize interactive multimedia cater to the individual needs of students in educational settings [34]. Dougiamas and Taylor (2002) noted that a key benefit of e-learning for educational institutions is the ability to access information from any location at any time [35].

To implement e-learning effectively, an "Adaptive Evaluation of Online Learning Environment" is crucial. This process uses computers and the Internet to create e-learning programs that help teachers deliver optimal instructions. According to [36], multimedia supports language learning by linking learners' real-world knowledge to audio-visual content. Such programs allow students to practice language skills tailored to their needs, making learning more dynamic and interactive [37]. Adaptive online tools boost motivation as students grasp concepts more easily through videos, images, text, and audio [38]. Artificial intelligence has moved from experimental to practical use in classrooms, enabling adaptive learning environments [39]. MOOCs and similar platforms offer high-quality, cost-effective education globally [40]. The COVID-19 pandemic accelerated the adoption of online learning, highlighting the vital role of technology in the future of education [41]. However, challenges remain in ensuring affordable and equitable learning for all.

Tailored teaching instructions are essential to improve individual learning outcomes and personalize the student experience. Research indicates that adaptive learning is more effective than traditional methods, such as lectures and seminars [42]. Adaptive Learning Environments face the challenge of achieving large-scale personalization globally. Systems such as ELaC, Java Guide, and JS Grader demonstrate this by customizing content to students' learning styles and preferences. These systems also support learners with varying programming skills levels. A systematic literature review explored the implementation of adaptive learning in both practical and theoretical settings, examining programming challenges, system advantages and disadvantages, and the technology, quality, and efficiency of adaptive learning systems.

2.3. COMPARISION OF OPEN SOURCE SOFTWARE FOR ADAPTIVE E-LEARNING

Compared to other open-source software, Moodle excels in evaluation criteria by offering essential features, such as content creation, student assessments, and learner tracking. [43] emphasizes the importance of offline learning due to limited network access for many young people. Moodle's extensive documentation helps developers easily utilize its tools, and its active community drives continuous innovation and responsiveness, as shown in Table 4. This vibrant ecosystem supports Moodle's leadership in educational technology, despite challenges in advanced customization and adaptability.

Currently, Moodle lacks AI-driven adaptive learning paths and is primarily used in North Africa, particularly in Morocco. Developing an adaptive module to personalize learning within Moodle could significantly impact education in this region. Skilled professionals are vital for successful implementation, as they provide expertise in integration, optimization, troubleshooting, and training. Key challenges include simplifying technical customization and improving the user interface to boost usability and engagement. Addressing these issues is essential for enhancing effectiveness and encouraging widespread adoption of these systems.

Canvas is an excellent choice for blended learning because of its adaptability and user-friendly interface, which simplifies navigation. Learning objectives were clearly defined, as shown by the quiz and assignment results. Canvas supports learning tool interoperability, enabling the seamless integration of third-party tools. Its cloud version, hosted on Amazon Web Services, offers a robust, native cloud solution. However, Canvas lacks creative tools and gamification features, which limits the learning experience. Open edX offers remarkable flexibility and a wide range of content creation tools, including image, animation, and video. However, its organization can be confusing, and it lacks compliance with standards such as SCORM and xAPI, reducing its competitive edge compared to platforms like Chamilo. Proper documentation is essential to support users during installation and usage.

Table 4: Comparison of e-learning open-source software systems [44]

Adaptive System	*Documentation*	*Language*	*Compliancy*	*License*
Moodle	To be accessible many languages (gait hub & web site)	Approximate 119 languages. Included French and Arabic	LMS, AICC, SCORM, AICC, xAPI and cmi5	General Public License GNU
Canvas LMS	To be accessible gait hub and web site	Include Arabic and French, support 37 languages	Cloud SCORM is dispatch xAPIthrough BLTI. SCORM 1.2 and supported by Canvas but AICC not.	General Public License GNU
Open source Edx	To be accessible gait hub & web site	The official language is English for Open Edx. Many more languages supported through Transifex	SCORM not supported but possible through integration of Cloud SCORM but Inherently AICC xAPI not supported. Those topic formats could be supported through LTI, Cloud SCORM Cloud and XBlock	Apache and AGPL license
Chamilo	To be accessible gait hub and web site	Including French and Arabic 26 languages supported	xAPI compliant, AICC and SCORM	GPL v3
Sakai	To be accessible many gait hub and web site	Including French and Arabic 19 languages supported	xAPI compliant and SCORM supported but. AICC not	ECL (Educ. Community License)
Ilias	To be accessible gait hub and web site	Including French and Arabic 51 languages supported	SCORM 1.2, SCORM 200, xAPI compliant AICC	GNU General Public License

Sakai LMS ranks lowest mainly due to missing key features, slow response times, and a non-intuitive interface hinders navigation. These findings align with [45], who recommended Moodle as the leading open-source LMS for its comprehensive features, strong community of over 80 million learners, and flexible e-learning support. While Open edX shows mixed results, Moodle excels in the overall user experience [46]. Canvas is frequently cited in higher education, but Moodle remains an emerging and popular platform [47],

The suitability of LMS features to meet user needs and accessibility is vital for students' satisfaction. Institutions evaluate LMS platforms based on specific criteria and their user requirements. A key gap is the lack of feedback systems that address learners' social and emotional states. Integrating content recommendations and sentiment analysis tools is essential [48]. Despite some limitations, Moodle has been identified as the best open-source solution for fulfilling requirements and benefiting many students.

3. DESIGN A FRAMEWORK FOR AILES

Bursilovsky and Peylo introduced the concept of adaptive systems in 2003, proposing an Adaptive and Intelligent Web-Based Educational System (AIWBES) to improve traditional web-based education [49]. The Adaptive Intelligent E-learning and Evaluation System (AILES) aims to tailor learning materials based on students' knowledge, preferences, age, education, behavior, goals, and likes. AILES relies on maintaining an efficient adaptive LMS that updates learner profiles to personalize content delivery, as shown in Figure 3.1.

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The system assesses students through a Domain engine, collecting personal data and evaluating them with tests at three levels: basic, moderate, and advanced, ensuring learning matches their knowledge level. The Result of conducting quiz or test is R2. The system automatic evaluates correct questions answers and wrong answer and not attempt questions are negative marking that will be subtract in total score(R2) of the test. Then add the result of both result (R1+R2) and the system select the Yk score of the student/learner which is the level of student/learner then system select the teachers course material according to the performance of the student. Selected course material b1 - - b2, m1 ~ m2 and a1 - - a2 is the basic level, moderate level and advance level: Yk = R1 + R2.

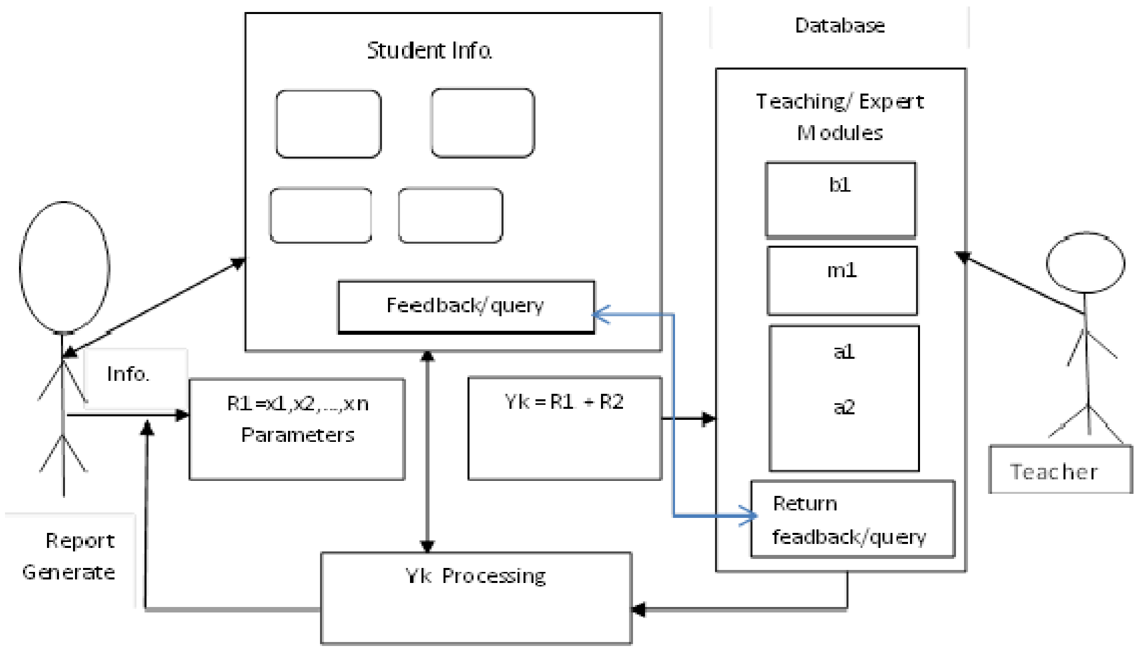

Figure 3.1 Knowledge assessment of student in adaptive e-learning system

3.1 Design a fuzzy controller for individual learner

There are many disadvantages to using only behavioural parameters or only questionnaires-based adaptive systems. The process of AILES must be adapted to incorporate both types of adaptive learning parameters while modelling the student/learner system. This process automatically evaluates learning parameters consisting of two phases: (i) exploring the behaviour parameters age, qualification, preferences, subject knowledge, and goals for each learner and (ii) using the result of behavioural parameters to conduct quizzes/pre-test using the 20 alternate objective type questions, each having 1 mark.

3.2 Assessment of the behavior parameters of student

The first phase of exploring the relevant behavioural parameters for each learner consists of classifying the accordance of behavioural parameters and defining parameter dimension values.

a) ***Exploring the Relevant Behaviour Each Learner:***

The student model contains factual and behavioural data about an individual learner/student, such as name, id, email_id, age, qualification of student/learner, background knowledge, and preferences regarding the course to learn. All these parameters test the behaviour of individual learners.

b) Evaluation of Parameters:

The LMS database stores this information, checks and validates these parameters, evaluates the result, and provides the result for the next step.

3.3 Conducting tests for the student/learner:

The second phase uses the results of the behavioural parameters. Initially, 10 objective types of questions were prepared, and each question carried one mark. The test was conducted, and the system automatically evaluated the results. Incorrect answers and questions that were not attempted were marked negatively. If the result is below average, average, or above average, learning materials (content, examples, and exercises) are provided. After learning each level completed then conduct exam of the learner These calculations are based on fuzzy system.

3.4. Algorithm to assess the performance of the behavior performance index for each learner using fuzzy logic:

To develop an algorithm for determining the behaviour index for each learner using fuzzy logic, we must define the parameters, linguistic variables, fuzzy sets, rules, and inference mechanism.

Algorithm Steps:

1. ***Initialize input-output variable***: Define linguistic variables and fuzzy sets for each Input and output variable. Take values for Age (A), Qualification (Q), Sub Knowledge(S)and output (BI)
2. ***Fuzzification***: Determine the membership grades for each input variable.
3. ***Rule evaluation***: The fuzzy rules are evaluated to determine the fuzzy output.
4. ***Inference Mechanism***: Apply the inference mechanism (e.g., Mamdani or Sugeno) to combine the fuzzy outputs.
5. ***Defuzzify***: Convert the fuzzy output into a crisp value to obtain the behavior index.
6. Let us discuss each of these steps.

Step 1: Define Input and Output Variables

- Input Variables of Behaviour index: Age (A), Qualification (Q), Subject Knowledge (S)
- Output Variable: Behaviour Index (BI)

Step 2: Fuzzyfication: Define the linguistic variable and fuzzy set for each input and output variable.

Student or Learner Age (A): If the Age of the student is 15 to 35 years, then the learning capability or performance of the learner is a higher behaviour index (BI) of 70% or above. When the Age of the Student is 35 to 50 years, the learning capability or performance of the learner is medium or average behaviour index greater than 40% to less than 70%. The Age of the student is 50 to 70 and above, and the learning capability or performance of the learner is a low behaviour index below 40%.

Student or learner Qualification (Q)

The qualification of the student HSC (11^{th} to12thS Class) then learner knowledge is lower, and the behaviour index is below 40%. The qualification of the student UG (13 -15 Class) then learner knowledge is average and behaviour index greater than 40% to less than 70%. The qualification of the student PG and PG plus (16 above Class) then learner knowledge is a higher index of 70%.

Subject Knowledge (S)

The subject knowledge of the Student Good then learner knowledge is a higher behaviour index point 0.7 (70%) above out of 1. The subject knowledge of the student average then learner knowledge is average behaviour index point greater than 0.4 (40%) to less than 0.7 (70%) out of 1.

The subject knowledge of the student is low or not, then learner knowledge is a lower behavior index point below 0.4 (40%) out of 1.

Output: Behavioural Performance Index (BI):

Step 3: Fuzzy Rules: Define fuzzy rules based on the inputs to determine the behavior performance index, as shown in Table 5.

Table-5 Fuzzy rules for behavior performance index

Age Group in Year (A)	Qualification (Q)	Subject Knowledge (S)	Behavior Index Performance Level (BI	Behavior Index Performance %
15 – 35	PG	Good	High	Above70

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15 – 35	PG	Average	High	40 to 70
15 – 35	PG	Low	Average	40 to 70
15 – 35	UG	Good	High	Above 70
15 – 35	UG	Average	Average	Above 70
15 – 35	UG	Low	Average	40 to 70
15 – 35	HSC	Good	Average	40 to 70
15 – 35	HSC	Average	Low	Below 40
15 – 35	HSC	Low	Low	Below 40
35 – 50	PG	Good	High	Above 70
35 – 50	PG	Average	High	Above 70
35 – 50	PG	Low	Average	40 to 70
35 – 50	UG	Good	High	Above 70
35 – 50	UG	Average	High	Above 70
35 – 50	UG	Low	Average	40 to 70
35 – 50	HSC	Good	Average	40 to 70
35 – 50	HSC	Average	Low	Below 40
35 – 50	HSC	Low	Low	Below 40
50 – 75	PG	Good	High	Above 70
50 – 75	PG	Average	High	Above 70
50 – 75	PG	Low	Average	40 to 70
50 – 75	UG	Good	High	Above 70
50 – 75	UG	Average	Average	40 to 70
50 – 70	UG	Low	Average	40 to 70
50 – 75	HSC	Good	Average	40 to 70
50 – 75	HSC	Average	Low	Below 40
50 – 75	HSC	Low	Low	Below 40

Step 4: Inference Mechanism: Apply fuzzy logic inference to determine the behavior index.

1. If Age(A) of the student 15 to 35 years and Qualification (Q) is PG and above and Subject Knowledge good (>70) then behavior performance index is high above 70%.
2. If Age(A) of the student 15 to 35 years and Qualification (Q) is PG and above and Subject Knowledge average (<40 and <70) then behavior performance index is high above70%.
3. If Age(A) of the student 15 to 35 years and Qualification (Q) is PG and above and Subject Knowledge low below 40 then behavior performance index is average 40 to 70%.
4. If Age(A) of the student 15 to 35 years and Qualification (Q) is UG and Subject Knowledge good (>70) then behavior performance index is high above70%.
5. If Age(A) of the student 15 to 35 years and Qualification (Q) is UG and Subject Knowledge average (>40 and <70) then behavior performance index is high above 70%.
6. If Age(A) of the student 15 to 35 years and Qualification (Q) is UG and Subject Knowledge below 40 then behavior performance index is average below 40%.
7. If Age(A) of the student 15 to 35 years and Qualification (Q) is HSC and Subject Knowledge good (>70) then behavior performance index is average 40 to 70%.
8. If Age(A) of the student 15 to 35 years and Qualification (Q) is HSC and Subject Knowledge average (>40 and <70) then behavior performance index is Low below 40%.
9. If Age(A) of the student 15 to 35 years and Qualification (Q) is HSC and Subject Knowledge below 40 then behavior performance index is Low below 40%.
10. If Age(A) of the student 35 to 50 years and Qualification (Q) is PG & above and Subject Knowledge good (>70) then behavior performance index is high above 70%..

11. If Age(A) of the student 35 to 50 years and Qualification (Q) is PG &above and Subject Knowledge average (>40 and <70) then behavior performance index is high above 70 %.
12. If Age(A) of the student 15 to 35 years and Qualification (Q) is PG & above and Subject Knowledge below 40 then behavior performance index is average 40 to 70%.
13. If Age(A) of the student 35 to 50 years and Qualification (Q) is UG and Subject Knowledge good (>70) then behavior performance index is high above 70%.
14. If Age(A) of the student 35 to 50 years and Qualification (Q) is UG and Subject Knowledge average (>40 and <70) then behavior performance index is high above 70 %.
15. If Age(A) of the student 35 to 50 years and Qualification (Q) is UG and Subject Knowledge below 40 then behavior performance index is average 40 to 70%.
16. If Age(A) of the student 35 to 50 years and Qualification (Q) is HSC and Subject Knowledge good (>70) then behavior performance index is average 40 to 70%.
17. If Age(A) of the student 35 to 50 years and Qualification (Q) is HSC and Subject Knowledge average (>40 and <70) then behavior performance index is Low below 40 %.
18. If Age(A) of the student 35 to 50 years and Qualification (Q) is HSC and Subject Knowledge below 40 then behavior performance index is Low below40%.
19. If Age(A) of the student 50 to 75 years and Qualification (Q) is PG or above and Subject Knowledge good (>70) then behavior performance index is high above 70%.
20. If Age(A) of the student 50 to 705years and Qualification (Q) is PG or above and Subject Knowledge average (>40 and <70) then behavior performance index is high above 70 %.
21. If Age(A) of the student 50 to 75 years and Qualification (Q) is PG or above and Subject Knowledge below 40 then behavior performance index is average below 40 to 70%.
22. If Age(A) of the student 50 to 75 years and Qualification (Q) is UG and Subject Knowledge good (>70) then behavior performance index is high above 70%.
23. If Age(A) of the student 50 to 75 years and Qualification (Q) is UG and Subject Knowledge average (>40 and <70) then behavior performance index is average 40 to 70 %.
24. If Age(A) of the student 50 to 75 years and Qualification (Q) is UG and Subject Knowledge below 40 then behavior performance index is average 40 to 70%.
25. If Age(A) of the student 50 to 75 years and Qualification (Q) is HSC and Subject Knowledge good (>70) then behavior performance index is average 40 to 70%.
26. If Age(A) of the student 50 to 75 years and Qualification (Q) is HSC and Subject Knowledge average (>40 and <70) then behavior performance index is Low below 40%.
27. If Age(A) of the student 50 to 75 years and Qualification (Q) is HSC and Subject Knowledge below 40 then behavior performance index is Low below 40%.

Step 5: Defuzzification: The fuzzy controller's component is tasked with converting the fuzzy selection index from the inference engine into a crisp value. The determination of the performance selection index for each learner's output variable is achieved through the implementation of the Centroid of area method by (Mamdani and Assilian, 1975) for defuzzification. These determined real values are stored in the performance index list. The Mamdani Fuzzy Inference System was used with the fuzzified input variables Age, Qualification, Sub-knowledge, and fuzzified output variable *PERFORMANCE* , and the Rule set as describes above. Mamdani's implication criteria are associated with linguistic values that describe the degree of inference action as explained by taking an example as shown in Figure-3.2. Apply fuzzy logic inference to determine the behavior performance index.

BI1= If A is Low-age Λ Q is PG Λ S is Good (RULE1)

BI2= If A is Med-age Λ Q is UG Λ S is Average (RULE2)

The "min" function typically serves as the operator, representing the output variable's value domain. The fuzzy control output BI is derived from aggregating all fuzzy subsets BIi, with their membership values A, Q, and S determined by their disjunction operation as described below.

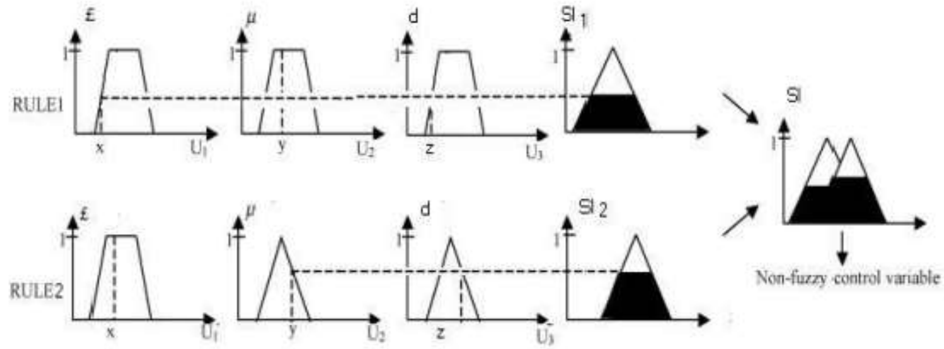

Figure-3.2 Fuzzy Inference Procedure

BI = BI1 V BI2 (Aggregation)

Here, the disjunction operator V is the "max" function.

Step 6: Behavior performance selection Index Criteria: The selection index for performance indicates the level of course material selection. The algorithm for selecting behavior performance index in the fuzzy controller ultimately establishes the level of course material by utilizing the behavior performance index for each learner. The learner with the highest selection index assigned the advanced course material.

4. RESULT AND DISCUSSION

The control surface of the fuzzy base controller illustrates the nonlinear conversion of the inputs to outputs. This transformation is represented by a nonlinear surface plot that shows the relationship between the input and output of the controller. For Fuzzy base controller with three dimensions, Figure 4.1 exhibits such a control surface. The undulating surface results from the interplay between the fuzzy rules and membership functions. The output selection index is calculated by considering the combined effects of the activated rules at any given moment.

The AILES system is a combination of student registration/login, behavior parameter assessment, and a tutor/evaluation module. After implementation, the system works satisfactorily from registration to course completion by the learner. At the time of registration, the learner provided initial information (name, email, age qualification, and subject knowledge). The entered information was stored in the database. The database design is not presented here. The behavioral performance index (BI) of the learner using AILES automatically provides the grade point and predicts which type of subject material is proved or selected by the learner.

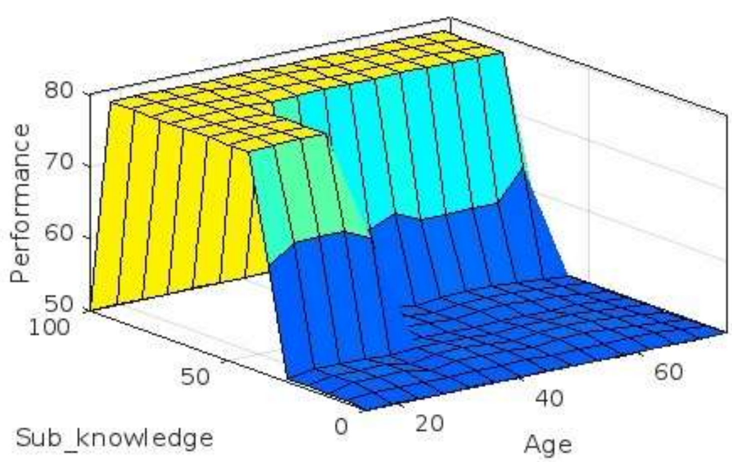

Figure 4.1: Nonlinear control surface of AILES for designed fuzzy rules

The system dynamically adapts the learning material based on student performance levels. If a student's performance is below average or scores 40% or less, the system provides the basic course content. This ensures that students grasp foundational concepts before moving forward. After studying the basic material, the students take an exam. If they score above 40%, they proceed to the next level; otherwise, they are instructed to repeat the course. During learning, if students face difficulties (e.g., solving an expression such as $z = (a + b) / (c - d)$), they can submit a query, and the system provides the solution as remedial support.

For students scoring above 40% and up to 70%, the system provides moderate-level content. Students must study, attempt exercises, and submit queries, such as $z = (ab) + (cd)$, if needed. If they pass the moderate-level exam with a score of more than 70%, they progress to the advanced course. Otherwise, they revisit the previous levels. Students scoring above 70% receive advanced content and, after completing it, take a final exam. A score above 75% confirmed successful course completion. If a student wishes to relearn the same subject, the system restarts the process with new content by a different author, enhancing learning diversity.

5. CONCLUSION AND FUTURE WORKS

With rapid advancements in web-based interactive technologies, distance learning has become increasingly accessible and widely adopted by educational institutions. Many digital courses are now built using SCORM-compliant learning modules. However, the abundance of available content often makes it difficult for learners to choose materials that best match their needs and interests. Research highlights the limitations of current e-learning methods and suggests the use of intelligent techniques, such as fuzzy logic, to improve personalization. Developing a framework for adaptive intelligent learning and evaluation could significantly enhance the effectiveness, adaptability, and efficiency of e-learning platforms, offering tailored educational experiences to diverse learners.

The journey to fully realize the potential of this framework is ongoing, with many possibilities for the future. Further research is needed to refine adaptive algorithms that accurately reflect individual learning styles and preferences. Additionally, integrating advanced technologies such as deep learning, natural language processing, and data analytics, along with leveraging diverse data sources, can significantly enhance the adaptability and intelligence of e-learning systems, making them more responsive and effective for personalized learning experiences.

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