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RESEARCH ARTICLE

A Novel Personalized Learning Framework With Interactive e-Mentoring

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ABSTRACT E-learning has established itself as a new alternative to conventional learning styles to accomplish the goal of education and learning for everyone. The classroom learning style is based on a ''one size fits all'' approach because, in a typical classroom environment, an instructor has to deal with several students at the same time. A similar problem goes along with the traditional learning management systems in which every student must learn the course devised by the instructor, within a specific timeline and achieve specific objectives, despite students' preferences and capabilities. The recent global pandemic has pushed educational institutes worldwide to recourse to an ''online-only'' mode of education and teaching delivery which has raised many challenges that need to be addressed. The existing e-learning systems fail to fulfill the expectations of a learner or an instructor in certain ways including the style of content delivery, mode of teaching, an adaptation of learner style that doesn't match with the teaching style, the content type, and above all the e-learning lacks to provide the e-mentoring capability to deal with the challenges a learner and an instructor's face during the learning process. This research aims to develop personalized learning by incorporating an intelligent e-mentor. The proposed e-mentor-based learning model is capable of customizing a course for individuals by automatically adapting it to their unique learning styles, preferences, abilities, existing knowledge, and expectations from the course. The outcome of the proposed model shows that e-mentoring not only increased learner satisfaction but also enhanced the learning process making it a preferred choice.

INDEX TERMS Learning management system, e-learning, online education, personalized learning, interactive systems, e-mentoring.

I. INTRODUCTION

The current outbreak of COVID-19 has shaken the world. Many industries and businesses around the world were affected including travel restrictions, closure of educational institutions, strict lockdowns, and quarantines. This pandemic has affected the lives of millions in different ways in different geographic locations worldwide. Beyond the immediate threat to health, unemployment, insecurity, etc., education is one of the sensitive areas which has been affected tremendously, worldwide [1].

The pandemic disrupted traditional learning environments, resulting in varied learning experiences and potential learning loss. Personalized learning can help students catch up by adapting instruction to their specific needs and paces [2]. The need for personalized learning in education is driven by the recognition that learners vary significantly in terms of their learning styles, paces, interests, and abilities. Traditional one-size-fits-all instructional approaches may not effectively meet the diverse needs of students.

Research has shown that students have diverse learning styles and paces. Project-based learning and problem-based learning both are well-known learner-centered approaches. Problem-based learning can be viewed as a subset of project-based learning, as one approach instructors can take is to task students with solving one or multiple problems within the project. Both learning approaches can be personalized as learner can choose to work on a project or problem that reflects their interests, strengths, and perspectives. Personalized learning adapts instruction to align with these individual

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differences, which can improve learning outcomes [3]. It provides students with autonomy and choice in their learning, fostering motivation and engagement [4]. Students are more likely to remain engaged and motivated when they perceive that their educational interests and needs are being catered to.

Education and technology-embedded education in post-pandemic has shown various new dimensions from video conferencing tools, to Learning management systems, to assessment models. This pandemic has pushed educational institutes worldwide to recourse to an "online-only" mode of education and teaching delivery. According to the United Nations Educational, Scientific and Cultural Organization (UNESCO) report 2020, a total of 1,190,287,189 learners are currently affected constituting 68% of the total enrolled learners worldwide because of temporary or indefinite countrywide educational institute closure [5]. According to the World Bank Report [6], as of April 8, 2020, due to the COVID-19 crisis, universities and other tertiary education institutions are closed in 175 countries and communities, and a total number of 220 million post-secondary students which 13% of the total number of students affected globally, and have had their studies significantly disrupted or ended. It is also found that earlier educational and learning models have not been that effective primarily when it comes to multiple students' engagement for the specific learning goal. Personalized learning equips students and institutions to adapt and continue learning even in challenging circumstances [6]. The traditional approach of learning through an existing learning management system has a fixed learning style of teaching using computer technology which has defined course development, assessments, grading features, and predefined users (teaches, students). In the traditional learning approach, students are forced to receive, learn, and pass the same designed course material and are also obliged to follow the same course structure, course plan, and course sequence despite their learning preferences, personal needs, learning style, or expectations levels [7]. This traditional LMS is a crude, non-intelligent, context unaware system based on instructor-centered learning. Furthermore, it is very difficult for an instructor to design or present a course having different expectations, and adaption styles, in a different sequence, while keeping user preferences, learning styles, and needs in mind [5]. Moreover, identifying the ideal learning strategy for every student or learner is also challenging and time-consuming. As well as to meet the expectations of every learner or student is another big challenge [6]. Many education researchers and pedagogy experts argue that the instructor-centered model is limited as a learning process since the concept of perfect learning requires the student contribution of the learner in classroom activities [9]. Hence this brings to new emerging problems of creating indicators whereby peer-to-peer learning and simultaneously collaborative teaching-learning environments be created that can comprehensively address the above issues. The evolution of social-cognitive development theories led to the creation, design, and delivery of educational curriculums in new ways considering the learner and his interaction with his peers through collaborative learning sessions [10]. The pandemic revealed the need for educational resilience in the face of future disruptions.

Post-pandemic education places a greater emphasis on preparing students with 21st-century skills. Personalized learning fosters critical thinking, problem-solving, and digital literacy, which are vital in the modern world [11].

The key contributions of this study are as follows.

1. We present a comprehensive literature survey and classification of existing learning systems.
2. We present a detailed comparative analysis of existing learning models, identifying the pros and cons of currently available systems.
3. Keeping in view the limitations of existing systems, a novel learning framework with e-mentoring features is proposed and implemented.
4. The proposed e-mentoring-based learning model is validated by the users using various experiments.

The rest of the paper is organized as follows: Section II discusses the existing models of teaching, and mentoring agent, their pros and cons, and gives insight into the related work. Section III discusses the research methodology based on two experiments conducted. Section IV covers the proposed model in detail. Section V is based on the eLMS prototype that is designed to validate the proposed model. Section VI concludes the paper with future recommendations.

II. LITERATURE REVIEW

To provide a better understanding of the issues that are being ignored in the current e-learning system and learning management systems, this section presents a detailed study of the wider and local context factors influencing the expectation and satisfaction of a learner and an instructor. The section is divided into three parts which are discussed below:

A. THE NEED FOR E-LEARNING SYSTEMS DURING OR AFTER ANY NATURAL DISASTERS

1) CONSIDERATIONS AND CHALLENGES AFTER COVID-19 PANDEMIC

According to the report by the World Bank Group [6] Impact of Covid-19 has affected many countries due to the closure of industries and businesses This crisis has affected the education as well as income of lower and middle-level income countries. Many countries have shifted to an online model of education and other forms of distance learning after the lockdown and closure of physical campuses which has raised many challenges including inadequately designed infrastructure, and lack of technical resources including broadband capacity and pedagogic capacity [12]. Many other forms of distance learning including the use of video conferencing tools, shifting physical classrooms to LMS, use of social network sites, and utilization of mail, phones, and various mobiles for communication, delivery, and assessment purposes are being tried and tested in this massive global experiment with off-site learning potential and modalities.

Furthermore, the detailed report [6] has listed that many short- and long-term challenges of tertiary education are exposed worldwide in the rapid assessment of the COVID-19 experience. This includes lack of resources for institutions, personal and academic challenges for institutions and students, demand for improved infrastructure to support continued distance and blended learning models, reduced mobility placing pressures to improve regional and local tertiary institutions, and much more. Subsequently, the report claimed that education systems are moving to online learning. The experimentation at the scale of adoption of online education triggered by the pandemic will speed up the learning curve of universities and provide them with a perspective to enrich campus-based programs with online elements in a way that aligns with demands from new generations of students and a world of work increasingly penetrated by technology.

The study emphasized various challenges that need to be resolved after a detailed survey of 98 countries [1]. The important factors that need to be addressed include the introduction of technologies and other innovative solutions and preparing students to manage their learning. The study further highlights the challenges education systems are facing to depend on online education as an alternative modality extracted from the data analysis from the recent survey of the administration of the PISA [13] have identified the critical challenges and factors faced by educational institutes of Jordan and Saudi during the COVID-19 crisis which can help and suggest researchers, policymakers, developers, or designers for the better adoption of e-learning systems. Qualitative research was conducted to collect and analyze data -using semi-structured interviews from six universities in Jordan and Saudi Arabia. A total of 30 students and 31 experts in e-learning systems were part of the experiment. The study concluded that five critical factors affect the usage of e-learning including technological factors, (e-learning system quality factors, cultural aspects, self-efficacy factors, and (trust factors, and the three main challenges [12] that hamper the usage of e-learning systems: change management issues-learning system technical issues and, financial support issues [14] have found the failure and success rate of imposed and unplanned distance learning in Covid-19 at INSA Toulouse, France. The survey was conducted with the different student groups of a 5-year program in various chemistry domains and teachers' feedback was also included. A few guidelines are also suggested to improve the distance learning and traditional learning models after identifying the success and failure rates. The suggestion includes the addition of virtual laboratories for experiment and practical exposure successfully in distance learning, gamification in distance learning to add motivation, paying attention to infrastructure, technology, and resources for better connectivity, provision of hardware and software resources, hybridizing the teaching method, redefining of the course structure. Furthermore, the emphasis was on redefining the role of traditional teachers as facilitators or a mentor, who should not be the sole owners of knowledge. The relationship of student-teacher also needs to be redefined and the role of a teacher should be flexible enough to devise their pedagogy.

The mode of online education in underdeveloped countries like Pakistan is not effective due to a lack of resources [15]. The study examined the effectiveness of online classes versus traditional classes and further highlighted the obstacle to online learning faced by higher education students in Pakistan. The survey was conducted with 126 undergraduate and postgraduates of the University. The hindrance to online education faced by students includes the lack of resources: internet, hardware, software, lack of interaction and connectivity, communication gaps between students and teachers, difficulty in group study, and campus socialization. The suggestion includes the redesigning of content, and content structure, focusing on the teachers' training for better content designing and delivery efficiency, and developing an effective delivery system. The educational institutes are only transferring learning content to their students through the digital world [16] but do not provide online education and are not focusing on content delivery methods. However, it is a reminder to have the latest technology in academic institutes and to have enough resources to provide digital education effectively. Furthermore, educational institutes should focus on the blended form of learning including online and face-to-face modes of teaching, along with strong student-teacher interaction, and have a strong infrastructure for human-machine symbiosis.

B. EXISTING MODELS OF TEACHING

The existing models of the education system include the conventional classroom education system and the Online Education System. Online education can be further classified into blended learning, distance learning, collaborative learning, etc. Various studies have shown the benefits and pitfalls of online learning over traditional learning and vice versa. Researchers and academicians' experiments on the learners and teaching experience in an online mode of education over the face-to-face learning environment [17].

1) CONVENTIONAL CLASSROOM EDUCATION SYSTEM

In a conventional classroom education, students are bound to be in a specific place and at a specific time. It facilitates face-to-face communication and interaction among students and teachers. Traditional education is based on a teacher-driven approach [18]. It has a fixed learning style and methodology which is based on the teachers' level of knowledge, structure, and design of content [19]. The traditional model of face-to-face classroom learning environment focuses on the passive mode and ignores the needs of an individual learner, furthermore, this mode of education lacks inculcation of critical thinking and problem-solving abilities among students [20]. Several studies have highlighted the advantages

TABLE 1. Pros and cons of traditional education systems.

Traditional Classroom Education System			
The Student's Viewpoint		The Teacher's Viewpoint	
Pros	Cons	Pros	Cons
Structured and systematic learning process. [22][9]	Costly [22]	Quick/spontaneous Feedback can be provided[9]	No flexible hours [23]
Face-to-face interaction[22]	Fixed class schedule[18]	Face-to-face interaction[20]	Fixed class schedule [9]
Quick feedback [18]	Physical presence is mandatory [20]	Instructor-centered approach[22]	Physical presence is mandatory[23]
Hands-on training [19]	Fixed time and Schedule[18]	Fixed teaching hours[19]	
	Fixed learning style[22] Instructor-centered approach[18]		

and disadvantages of the traditional education system used worldwide [21].

Table 1 below categorizes the pros and cons of the traditional education system concerning student's and teacher's view point.

2) ONLINE- EDUCATION SYSTEMS

Online education or e-learning is a contradictory term that has been widely referred to in many studies and research to define the learning process with the blend of computer systems, technologies, software, hardware, internet, and infrastructure [24]. Several studies have highlighted the benefits and weaknesses of the online education system used worldwide. Online learning can be accomplished through a distributed model of hybrid learning and in the form of distance education [20]. To have a successful online content delivery benefits and limitations to the students, and organizations should be balanced. Several studies have explored the advantages and disadvantages of traditional classroom systems and online education systems from students' or learner's perspectives [19]. However limited attention has been given to emphasizing the advantages and disadvantages of learning from teachers' perspectives [21]. Table 2 below categorizes the pros and cons of the online education system keeping student and teacher's viewpoint.

E-learning has appeared as an encouraging solution to lifelong learning [9] and it is the future of the education industry. It will overcome many drawbacks of a fixed physical classroom learning environment that includes less paper and reduction of heavy bag packs, faster delivery to many students across the world with no limitation of time and space. It will provide instant access to content exactly at the point where it is needed. However, a continuous effort is required to overcome the pitfalls and hindrances of facilitating students in an effective online learning environment.

TABLE 2. Pros and cons of online education systems.

Online Education System			
The Student's Viewpoint		The Teacher's Viewpoint	
Pros	Cons	Pros	Cons
Cost-Effective [23]	Slow feedback from instructors[23]	Content availability [21]	More time-consuming to prepare a lecture [25]
Flexible learning hours and schedules[22][26]	Lack of Face-to-face interaction[21]	Flexible teaching hours and schedules [17][26]	Not suitable for many courses[25]
Online availability irrespective of time and location [22]	Unsteady attendance of learners. [21]	A single lecture can serve many classes[19]	Cheating prevention is difficult [19][26]
Learner-centered and self-paced [22]	Requires self-motivation [9]	Ideally accessible to a worldwide audience [21]	Assessments and individual feedback are time-consuming[21]
The content is accessible globally[22]	Required time management skills [19]	No need for physical space, time-independent in the asynchronous mode of teaching [21]	

C. MENTORING AGENTS

An intelligent artificial system AI-Medic is developed for autonomous medical mentoring [27]. The system uses an encoder-decoder neural network to predict surgical instructions given the current view of surgery. The AI-Medic was trained using DAISI, a dataset to train AI algorithms that can act as surrogate surgical mentors. The dataset includes 17,339 color images and captions that provide step-by-step demonstrations for performing surgical procedures from 20 medical disciplines. To assess the system, the instructions predicted by the AIMedic were evaluated using cumulative BLEU scores and input from expert physicians (BLEU (BiLingual Evaluation Understudy) is a metric for automatically evaluating machine-translated text. According to the BLEU scores, the predicted and ground truth instructions were as high as 86 +/− 1% similar. Moreover, expert physicians considered that randomly selected images and their predicted descriptions were related. The results from this work serve as a baseline for future AI algorithms assisting in autonomous medical mentoring.

The concept of MentorPal is taken from two early project approaches [28] that include New Dimensions in Testimony (NDT) and the Personal Assistant for Life-Long Learning (PAL3). The user interface design for MentorPal was developed inside the PAL3 framework which controlled the overall user flow (e.g., account creation, logging). The PAL3 project is an adaptive learning platform, with an interactive learning assistant (Pal). The long-term goal of PAL3 is to track a learner's progress and provide personalized learning recommendations from a library of learning resources based on performance and career goals. MentorPal emulates conversations with a panel of virtual mentors based on recordings of real STEM professionals. Students freely ask questions as they might in a career fair, while machine learning algorithms respond with best-match answers. A panel of four mentors is taken to cover the main career interests. To evaluate the system's impact on student outcomes a usability study was conducted. 31 High school students were taken as participants to evaluate the system's performance.

Results show that to have a question-and-answer conversation about career fields it is required to have a 5 to 20-question set of approximately 400 responses. From the results, it was observed that a panel of four mentors is insufficient to cover either the main career interests or diversity representation of even 31 students [28]. A distributed architecture for mentoring is presented [27]. The proposed architecture consists of different modules each having specific task(s) like Ias2peer, blockchain service registry, etc. On top of the proposed architecture authors set up a chatbot-based interface for end-users. Conversational chatbot strategies for learning agile and scrum development are introduced in this study [28]. A web-based interface was developed to guide learners with knowledge paths so they can learn the higher education curricula for agile software engineering. 200 students of undergraduate level participated as a testbed for the proposed approach. The key challenges of the learning domain are highlighted in the study [29]. Moreover, considering the identified challenges, the authors proposed an intelligent mentoring service architecture.

The aim of Neumann et al. [30] is to provide one-to-one mentoring to the student that supports education sciences in their self-study. For this purpose, two chatbots namely FeetBot and LitBot are developed and evaluated that are specifically designed to deal with seminar literature and recommended study material. The chatbots were used by 700 students for 1 year. The purpose of these chatbots was to provide a mentoring tool to students that can help and support them in self-study activities. The lit bot used issue-specific annotated knowledge graphs. T-MITOCAR software was used to transfer the text to a graph which was taken for an educational science course. The conclusion section stated that for personalized learning, adaptive learning is one of the key concepts. The author has also mentioned that in the future other courses in higher education can be developed and improved with the use of mentoring bots. Results show that the proposed approach provided significant improvement in digital mentoring to students. The paper presents the concepts, implementation, and evaluation of intelligent mentoring bots that are implemented as chatbots and integrated into learning management systems [31]. These intelligent bots are helpful to guide and help students in eLearning. One chat is integrated into Moodle wiki. The bots are designed to provide answers to simple frequently asked questions and provide feedback on text submissions. Two evaluations were performed. First was the developer's evaluation to check the usability of new features created in bots. Eight participants were involved in the evaluation process. The result shows that the participants generally liked the Rasa NLU model training interface and found it easy to use. The second was the pedagogical evaluation in which the bot's usage was tested. According to the responses received by the participants' bots did not always provide the right answers to the questions and later questions had to be rephrased to get the desired results. Results further show that bots are good at providing mentoring assistance and can be used to assist in teaching. Alamri et al. [31] provide an extensive literature review on personalized learning with a blended learning environment in higher education. Additionally, the author of the paper discusses the implementation attempts of technology platforms that are facilitating personalized learning. The paper highlights the need for higher education to shift from a teacher-centered to a learner-centered approach. A total of 84 pieces of literature were added for this systematic research. The research results uncovered three emerging technology models that support and guide the design and development of personalized learning platforms in higher education. These include open digital badges, competency-based learning technology, and adaptive learning technology. These models can be integrated simultaneously or can be implemented independently to support personalized learning. Recommendation for future research shows that motivation and student engagement factors should be measured in personalized learning. Alamri et al. [27] highlight that personalized learning effectiveness can be measured through learning outcomes.

Table 3 below the pros and cons of current mentoring agents. A gap analysis reveals the shortcomings of existing mentoring models, underscoring the necessity for an e-mentoring model that enhances the learning process.

III. RESEARCH METHODOLOGY

To support the problem statement by identifying the issues and weaknesses in the existing learning management systems two experiments are designed using a mixed method approach that includes both qualitative and quantitative methods. The qualitative data support the quantitative data analysis and results. The result obtained is triangulated since the researcher utilized the qualitative and quantitative data types in the data analysis. The study area, data sources, and sampling techniques are discussed in this section. The first experiment was performed in various departments, in various disciplines, and from various knowledge levels learners of multiple institutions to get a better understanding of the problem. The first experiment consisted of a series of well-structured questionnaires for learners and a semi-structured interview with the instructors. The second experiment consisted of a laboratory experiment performed by a biomedical student at a local university.

TABLE 3. GAp analysis of mentoring agents.

Pros and Cons of Mentoring Agents	
Pros	Cons
Knowledge Transfer: Mentoring agents, such as AI-Medic, can transfer knowledge and expertise to individuals in specific fields, such as surgery or STEM professions. This can help accelerate learning and skill development.	*Insufficient Mentor Coverage:* Some mentoring agents, such as the panel of four mentors in MentorPal [26], may struggle to cover the diverse career interests and provide adequate representation for a large number of learners. This can limit the effectiveness of the mentoring program.
Personalized Learning: MentorPal and other mentoring agents can provide personalized learning experiences by emulating conversations with virtual mentors. This individualized approach can cater to specific career interests and address learners' questions effectively	*Lack of Human Interaction:* While mentoring agents can offer guidance and support, they may lack the human interaction and emotional connection that can be beneficial in traditional mentoring relationships. Some learners may prefer the interpersonal aspect of human mentors.
Usability and Accessibility: Chatbot-based mentoring agents, like the ones discussed in the literature review, offer a user-friendly interface that allows learners to access mentoring services conveniently. These agents can be integrated into learning management systems, making them easily accessible to students.	*Accuracy and Reliability:* Mentoring agents, especially chatbots, may not always provide accurate or reliable answers to learners' questions. Participants in the evaluation process mentioned that bots did not always provide the correct responses, requiring rephrasing or multiple attempts to get desired results.
Scalability: Mentoring agents have the potential to scale their services to accommodate a large number of learners simultaneously. They can handle multiple inquiries and provide prompt responses, ensuring learners receive timely guidance and support.	*Bias and Limitations*: Unconscious bias can affect the responses and guidance provided by mentoring agents, potentially limiting diversity and inclusivity. It is important to ensure that mentoring agents are developed with careful consideration for bias and are regularly updated to address limitations.
Enhanced Learning Outcomes: The use of mentoring agents has shown improvements in student outcomes, as seen in the usability study conducted with high school students. Personalized feedback, guidance, and mentoring assistance contribute to better learning outcomes.	*Learning Engagement and Motivation*: While mentoring agents can assist in teaching and provide guidance, they may not always effectively address motivation and student engagement factors, which are crucial for personalized learning. Measuring and addressing these factors should be considered in future research

TABLE 3. *(Continued.)* GAp analysis of mentoring agents.

	Limitations in Real-Time Interaction: Mentoring agents, especially those based on pre-recorded responses or chatbots, may have limitations in real-time interaction. Learners may not receive immediate feedback or responses to time-sensitive queries, which can be a drawback in certain learning scenarios.
	Ethical Concerns in AI-Medic: While AI-Medic demonstrates promising results for autonomous medical mentoring, it's essential to address potential ethical considerations related to patient safety and data privacy. The use of AI algorithms in medical contexts must be carefully regulated and validated to avoid harmful consequences.
	Technology Dependence in Self-Study Activities: While FeetBot and LitBot aim to support students in self-study activities [30], the reliance on chatbot technology might lead to reduced student engagement or dependency on the bots rather than fostering independent learning skills.
	Scalability Challenges for Chatbot-based Mentoring: The chatbot-based mentoring approach in [30] faced challenges in providing the right answers to participants' questions. It required rephrasing questions to get desired results, indicating potential limitations in handling complex queries and ensuring accurate responses.
	Learning Outcome Evaluation in Intelligent Bots: Evaluating the effectiveness of intelligent mentoring bots, as mentioned in [31], might require careful measurement of learning outcomes beyond simple question-and-answer interactions. Assessing long-term impacts on student learning and performance is crucial for comprehensive evaluation

TABLE 3. *(Continued.)* GAp analysis of mentoring agents.

	Limited Personalization in Intelligent Mentoring Bots: Despite providing significant improvement in digital mentoring, the mentoring bots described in [32] might have limitations in personalizing the learning experience for each student. The lack of personalized learning paths can hinder the effectiveness of the mentoring bots in catering to diverse learning needs.

A. EXPERIMENT I: QUESTIONNAIRE-BASED SURVEY

Experiment-I is designed to gather statistical information about the learners' opinions, attitudes, and experiences of learning through learning management systems by the structured set of questions designed. The objective of this questionnaire-based quantitative survey is to identify the student's perceptions of online learning through learning management systems. The participants were from diversified backgrounds with various knowledge levels, skills, etc. The study population consisted of active learners and students who were enrolled in some degree program or certification or self-learning through learning management systems. The population of data was collected from Primary learners, Secondary learners, Undergraduate, Graduate, and Postgraduate students, Skill and Vocational Certification learners, and learners enrolled in religious education. To conduct a research survey 23 questions were designed using a Survey Legend tool to design a questionnaire survey. Sixteen questions were designed to investigate the learner's perception of the issues of existing learning management systems. A total of 900 students from various countries have participated in the survey so far. Out of 900 results, 117 responses were discarded due to not submitting the complete answers.

1) DESIGN AND RESEARCH ANALYSIS

Experiment-I is divided into two sections. The first section comprises the respondents' demographics. Both males and females were chosen as participants. Respondents who were taken as subjects are from various backgrounds, education skills, and levels of learning, belong to multiple educational institutes, and belong to various years of study. Further, the data is also collected based on the learning management systems and the video conferencing tools used for the course learning by the respondents. Participants had the option to select the course as per their preference. Section two is based on the set of questions that were designed to inquire about the experience of online learning through learning management systems. Also, it highlights the issues respondents have faced during learning through existing e-learning systems.

TABLE 4. Demographic Data: gender, age, year of study & academic status.

		Frequency	Percentage
Gender	Male	449	57%
	Female	334	43%
Age			
	Below 17	61	8%
	17-27	496	63%
	28-38	168	23%
	39-49	37	5%
	50-60	21	2%
Year of Study			
	Less than a Year	23	3%
	First Year	192	24%
	Second Year	177	23%
	Third Year	239	30%
	Fourth Year	59	8%
	Fifth Year	37	5%
	Other	56	7%
Academic Status			
	School Primary Level(1-5)	2	0.3%
	School Middle Level(6-8)	15	2%
	School Secondary Level(9-10)	22	3%
	Higher Secondary Level (11-12)	22	3%
	University Education- Undergraduate Level (13-16)	393	50%
	University Education- Graduate Level (17-18)	150	19%
	University Education- Post Graduate Level (Ph.D.)	35	4%
	Vocational Training/Skill based Program	70	9%
	Madrassah Education	40	5%
	Any Other Certification or Program	34	4%

2) PARTICIPANTS DEMOGRAPHICS

According to the survey results the active participation is 63% belongs to those who were between the age bracket of 17 to 27 and the second-highest percentage of participants is 23% and they were people aged from 28-38 percentage. 4% of participants belonged to the age bracket of 38 to 48. The least participation is from the age of 50 to 60 and below 2 that is 2% and 8% of respondents were below age 17 as discussed in Table 4.

Students were inquired about their learning goals or objectives which they had after learning the course. The answer was designed to keep the most common perspective associated with learning any course or content. According to the responses, 8% of participants were those who were studying the course to get a professional degree or certificate. 8% of participants were those who had the only objective to learn the course to get good marks or grades. According to the responses, 14% of the participants were enrolled in the course to get a better and deeper understanding of the theoretical concepts. According to the 18% of participants, their personal learning goal to learn the course was to apply the learning tool, and theoretical concepts practically or in a professional environment. 22% responded that they have studied a specific course to learn new skills and to bridge the knowledge gap. 30% of the participants are those who have selected the option all the above means according to them their personal learning goal or objective after learning the course matched all the given requirements.

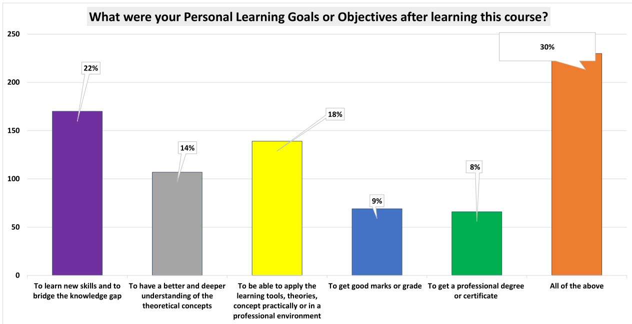

FIGURE 1. Percentage of learning goals or objectives achieved after learning the course..

Fig 2. depicts the confusion matrix that shows the choice of answer and their percentage of being selected together with the other options. Students were asked about their learning goals or objectives from the course or content provided to them and in the given options. Option A *(the personal goal is to learn the skills and bridge the knowledge gap)* depicts the high concurrence with option D (*to get good marks or grades in the course they chose to learn)* and vice versa. Further to that option B *(have a better and deeper understanding of the theoretical concepts)* has the-second-high concurrence with option C *(to be able to apply the learning tools, theories, concepts practically or in a professional environment)* and vice versa. Option C has a high concurrence of chosen together with option A (the personal goal is to learn the skills and bridge the knowledge gap). In addition to that, option E *(to get a degree or certificate)* has a high concurrence with option C. The confusion matrix illustrates that options *A, B, and C* have a high preference and concurrency of being opted together.

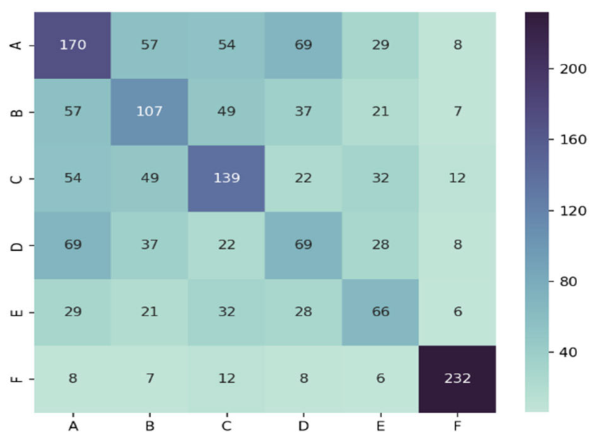

FIGURE 2. Confusion matrix of personal goals or objective to learn the course.

Fig 3. shows the data about how much students are satisfied after learning the course. Did they achieve the goal or objective after learning the course and did the course cover the content they were expecting? 31% were those who said their expectations were not at all met. 44% said the goal was achieved less than they were expecting. According to 19% of the participants, their expectations to learn the course matched their goals. 4% were satisfied and said that their expectations were exceeded and accordingly to the rest of the 3% their satisfaction was greatly exceeded.

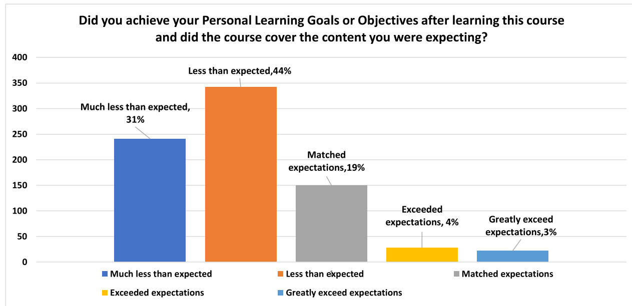

FIGURE 3. Percentage of expectations achieved after learning the course.

A few questions were designed to ask how course contents are designed and presented to students by the instructors. Fig. 4 illustrates that 43% of participants could not understand the objectives of the topics covered in the course due to the lack of logical and sequential arrangement in the course contents. Additionally, 48% mentioned that the topics were moderately arranged clearly and logically. Only 9% of the participants were able to understand the objective of the topics being covered during the course because the course contents were completely arranged logically and sequentially.

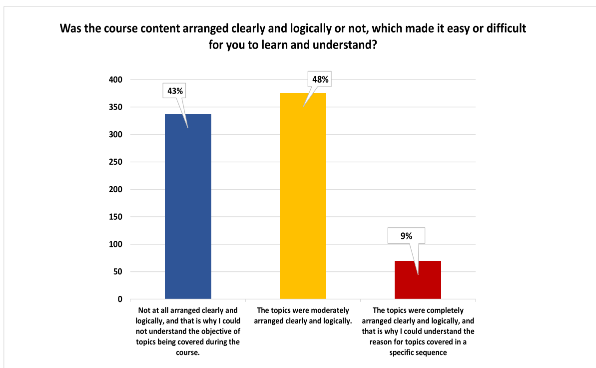

FIGURE 4. Percentage of course, content arranged logically or not.

Participants were asked how effective their assessments were. As shown in Fig 5. 38% of participants answered that their mistakes were not identified by the instructors, nor did they receive any feedback on given quizzes assignments, or class activities. 13% of the participants said that the feedback they received was too late to be useful for them. 25% said that the feedback they received was not very quick, but it was relevant and helped them to understand their mistakes. According to 24% of the participants, they received feedback on their assessments on time which helped them identify and understand their mistakes.

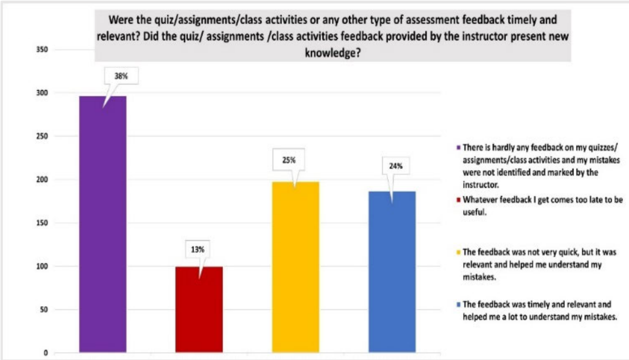

FIGURE 5. Percentage of the expectations achieved from assessment through LMS.

A few questions were designed to understand the flexibility and personalization aspects of learning and how much freedom they have in the conventional learning system as depicted in Fig 6. 48% of the participants believe that they do not have the freedom to learn or skip whatever they want according to their need for learning. They are restricted enough to learn whatever content is presented to them by their instructors only. 38% of participants believe that they have partial freedom to learn according to their choice of learning and according to their needs or preferences. Only 14% of the participants stated that they have the complete freedom to learn according to their choice of learning topic and they can choose or skip the topic according to their needs or preferences.

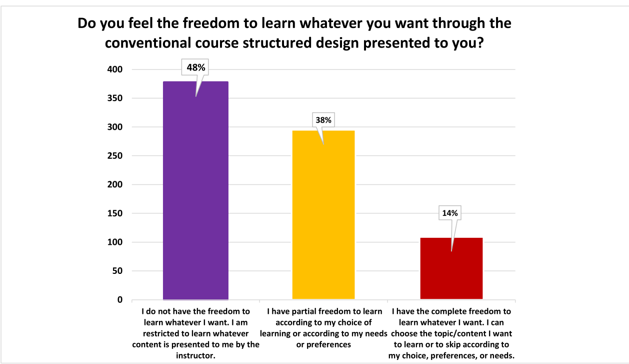

FIGURE 6. Participants' percentage of freedom to learn through conventional learning system.

Students were asked about how much freedom they have in the conventional learning system concerning time-bound as depicted in Fig 7. According to the survey results 72% of participants believe that they do not have the freedom to learn according to their own pace of learning and according to the amount of time they need to get expertise in any specific topic. Only 28% of the participants stated that they can adjust their learning pace according to the amount of time they need.

Fig 8. shows the result of the level of student interaction with their peers or instructors they had while learning through LMS. According to 72% of the interactivity with

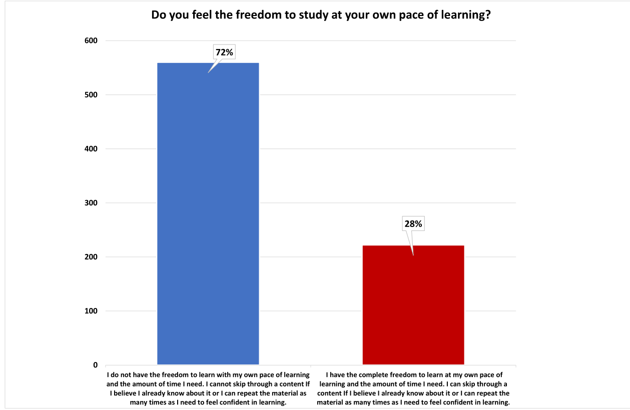

FIGURE 7. Participants' percentage of freedom to study through existing learning systems.

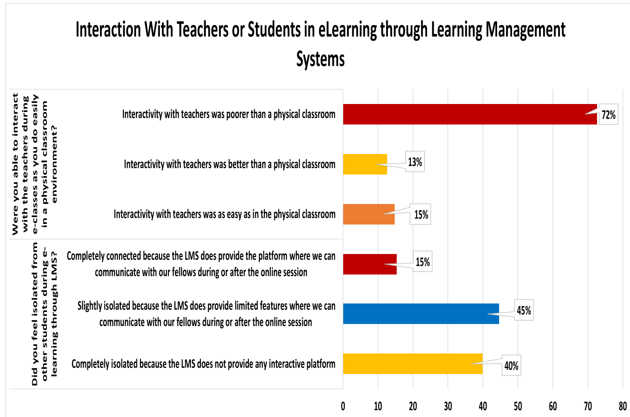

FIGURE 8. Percentage of student interaction with other students or instructors in eLearning through LMS.

their instructors was poorer when compared to a physical classroom environment. 13% of the participants argued that interaction with their instructors was better than physical interaction in a classroom environment while according to the rest of the 15% of participants interaction in an e-learning environment is as easy as in a classroom environment and there is no such difference. Participants were further asked how connected or isolated they feel when they must interact with their peers or other students. 40% of the participants said that they feel completely isolated from their peers because the learning management system does not provide any interactive platform by which they can communicate or interact with other students during or after the online session. 45% of the participants believe that the existing learning management system does provide limited features by which they can communicate or interact with other students during or after the online sessions. 15% of the participants argued that the learning management system provides complete features by which they can easily communicate or interact with other students during or after the online session. Figure 9 below shows the difference in the interaction of students with other students and instructors.

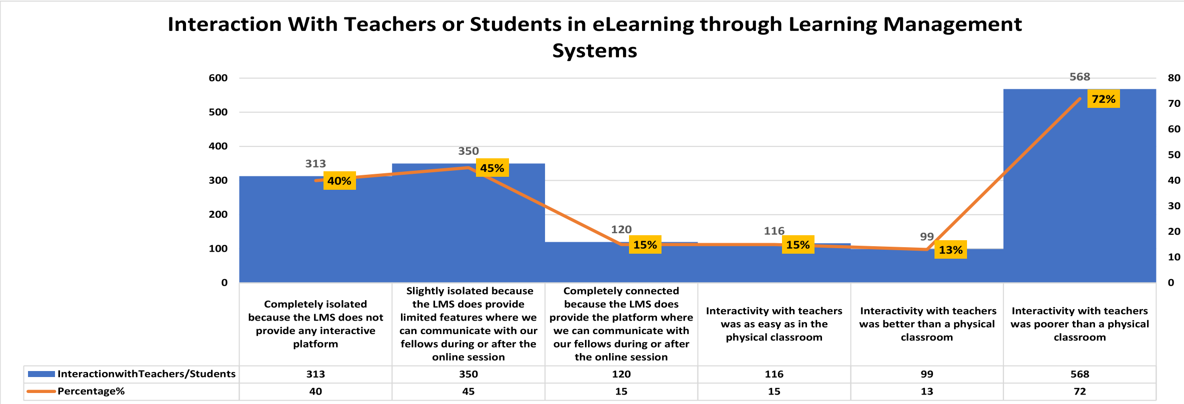

FIGURE 9. Clustered column line showing the difference in interaction of students with other students and instructors.

To get a deeper knowledge about the issues in the existing learning management systems, participants were asked how they perform group activities or assignments and does the LMS supports teamwork or group learning with other students during eLearning as depicted in Figure 10 below. 64% have stressed the issues they have faced while performing group activities or tasks in the existing learning systems. 36% of the participants believe that the LMS does support teamwork and group learning activities.

A few of the questions were designed to inquire about the reactions to taking an online course and if they had a choice to learn it physically would they prefer to learn through a conventional learning system or would they prefer eLearning? Various responses were received related to why students are not willing to take the course online as shown in figure 12 and 13. According to 24% of the participants, LMS does not support teamwork or group activities. 21% of the participants believe that online learning is difficult as compared to physical learning due to many issues that exist in the learning systems. 14% of the participants believe that they would not prefer to take online courses because the theoretical courses can be learned easily but practical or lab-oriented courses are difficult to learn online or through eLearning systems., 9% of the participants stated that they would not prefer to learn online because the lecture delivery tools like Google Meet, Zoom, WebEx, etc. are not good enough to support online learning efficiently and effectively. 6% would not like to learn online because of the poor assessment and grading methods in the existing learning management systems. According to 12% of the participants' online feedback on class activities like mathematical or programming tasks, drawing, or other skill-based activities is difficult to access and evaluated by the instructors or even peers. Only 14% of the participants believe that they would prefer to take the course online through learning management rather than physical because learning the course online system is easy and they have not faced any specific issues highlighted above.

Fig 11. below is the confusion matrix about the preference of learning courses online or not and the choice of answer and their percentage of being selected together with the other options. Students were asked whether would they prefer to take the courses online or not and in the given options, option A *(No, I will not prefer to take this course online because the course is difficult to learn online as compared to physical)* depicts the high concurrence with option B *(No, I will not prefer to take this course online because the theoretical aspects can easily be grasped online but the practical or lab oriented courses are difficult to learn online).* Further option B has the highest concurrence with option C *(No, I will not prefer to take this course online because it does not support teamwork or group learning)* and vice versa. Option D *(No, I will not prefer to take this course online because the lecture delivery tools are not good enough to support online learning)* has a high concurrence of chosen together with option A. In addition to that, option E *(No, I would not prefer to take this course online because the grading and assessments are not good/poor in the learning management systems)* has a high concurrence with option B.

The confusion matrix illustrates that option B has the overall highest concurrence of appearing together with other options followed by option A. The cumulative results reveal that 85% of the participants are not satisfied to learn online through exiting learning management systems and they have faced innumerable issues. 15% are satisfied with eLearning through existing learning systems.

Further to that, participants were also asked if they had the choice to leave the course, would they or would they continue online learning, and what are the reasons behind that? Fig 14 below discovered that 18% of the participants would have left the course because of the difficulty in understanding the lecture or due to the unmatched teaching style with their preferences. 19% of the participants leave the course if they were given the choice because learning online is difficult. 7% found it boring to learn online due to a lack of motivation through learning online. 19% found it difficult to learn online because of communication and interaction issues with peers and instructors. According to 6% of the participants quality of the examples presented during the

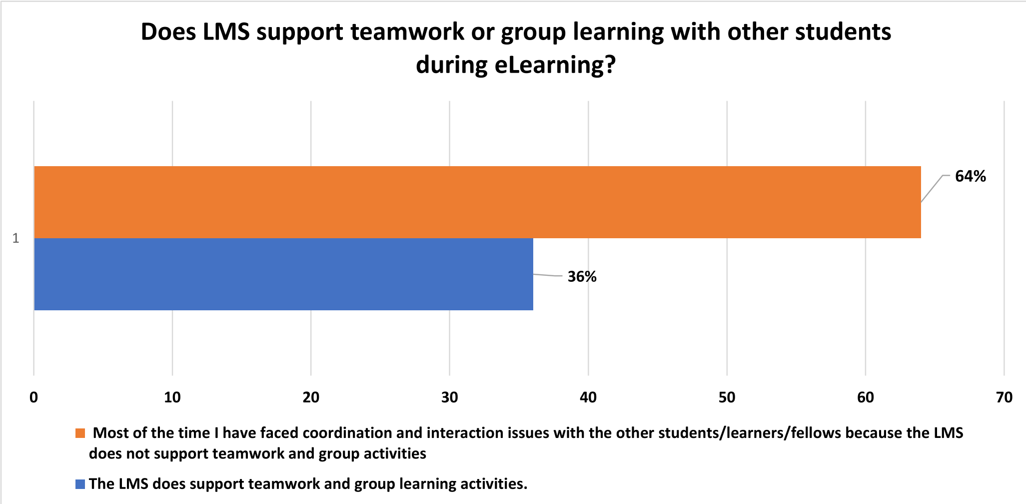

FIGURE 10. **Participants' percentage of teamwork or group learning supports by existing LMSs.**

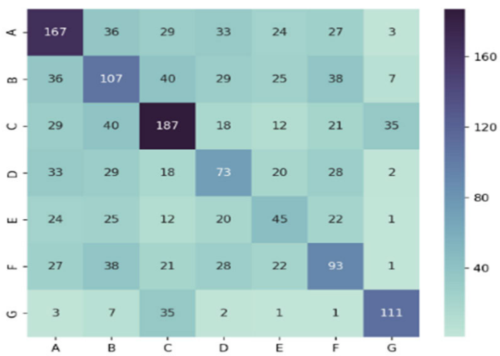

FIGURE 11. **Confusion matrix about preference of learning online or not.**

course was poor and they were unable to understand the way it was taught. 21% of the participants believe that they would have continued learning the course even if they had a choice to leave because learning courses online through a learning management system is effortless and they have not faced any specific issues highlighted above. The cumulative result shows that 79% of the participants were willing to leave the course if they had the choice because they faced uncountable issues learning through learning management systems. 21% would not have dropped the course as the results show.

Fig 15. below is the confusion matrix that describes students who were asked if they had given a choice to leave the course in the middle without completing it, would they opt for the option or not. Students were asked whether would they prefer to take the courses online or not and in the given options, option A *(Yes, because I could not understand the teaching style (lecture delivery method))* depicts a high concurrence with option B *(Yes, because the course/content was difficult to understand Online)* and vice versa. Further to that option C (Yes, I because the option was too boring) and Option D *(Yes, because there was no interactivity during class lectures)* have the highest concurrence with Option B. Option E has the same concurrence of chosen together with Option A and Option B. The confusion matrix indicates that option B has the overall highest concurrence of appearing together with all the other options.

Lastly, the participants were asked about the overall online learning experience they had through the existing learning management system and lecture delivery tools to support learning. Fig 16. shows that 20% of the participants rate the experience as bad because of collaboration and commination issues and lack of face-to-face communication. 11% of the participants believe that the online learning experience was bad because the course structure was too rigid and too lengthy to be digested in a specific amount of time. 13% of participants said that content delivery is difficult to understand in an e-learning environment. 10% of the participants stated that the online learning experience is bad because there were no personalization aspects associated with the choice of content structure or time adjustment and does not support individuals' needs or preferences. 6% of participants believe that the overall learning experience is bad because grading and assessment are not helpful for them. 7% of the participants had a bad experience learning online because according to them the GUI does not support teamwork or group learning, and the instructor cannot give immediate input on provided class activities on a run-time basis. According to 9% of the participants, there are very limited options in an existing learning system, and this is the reason learning online is difficult. According to 7% of the participants, the overall online learning experience is the worst because it has all the listed above issues. The cumulative results prove that 18% of participants had a bad experience overall learning online through learning management systems because they believed that they had not found any difficulty and their learning outcomes achieved what they had expected from

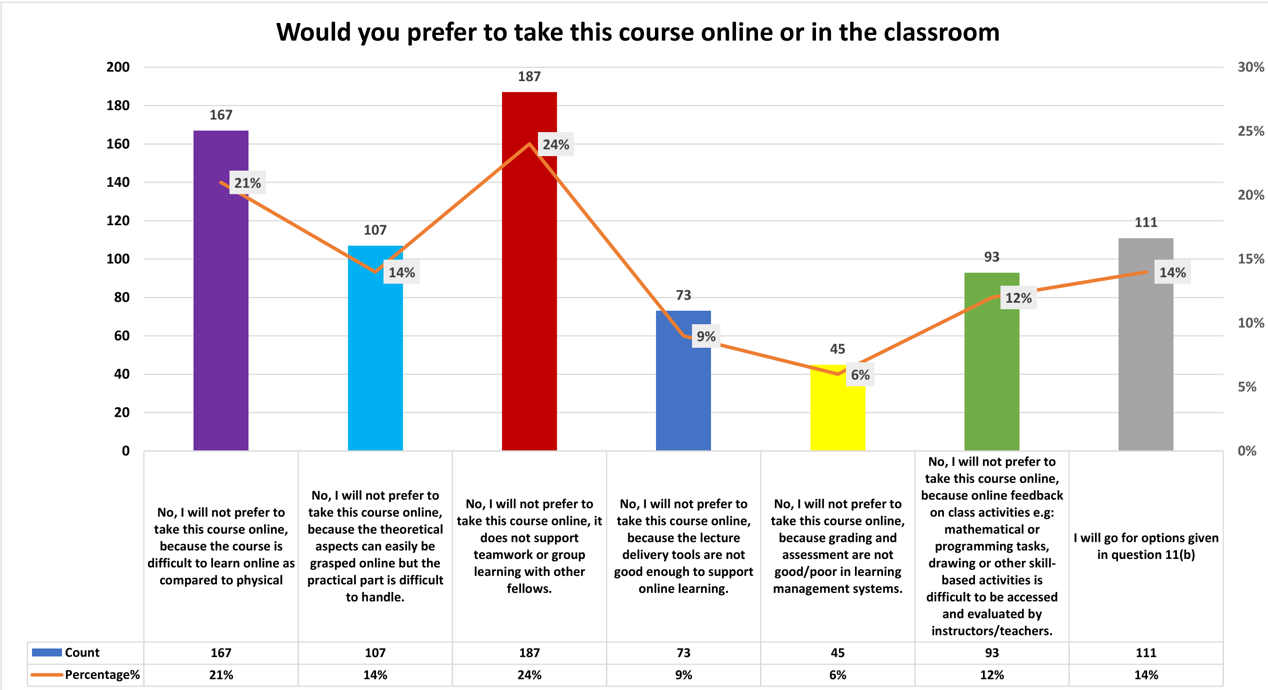

FIGURE 12. Percentage of students' preferences to take class in the conventional classroom environment.

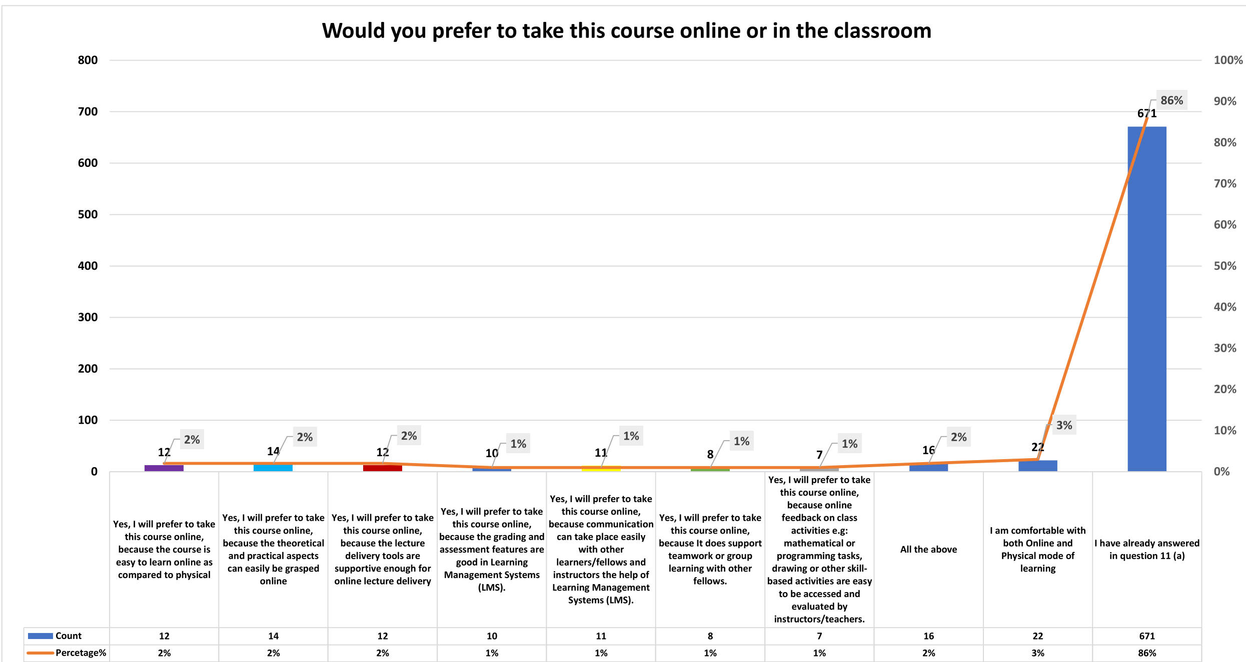

FIGURE 13. Percentage of students' readiness to take classes online through LMS.

the course. 82% of the participants had a bad experience overall learning online through learning management systems because of uncountable issues they have faced due to which they could not achieve the learning outcomes and their learning objectives were not met.

7% of participants claimed that overall, they had a good experience learning online because the course structure was flexible, and they were able to adjust their learning path accordingly and time adjustment can be done according to their needs or preference. 6% had a good experience learning online because they did not face any difficulty understanding the concept of the course/content. The remaining 6% rated their experience as good because they didn't face any communication or interaction issues.

Fig 17. uncovers the confusion matrix that demonstrates the overall learning experience of participants through the

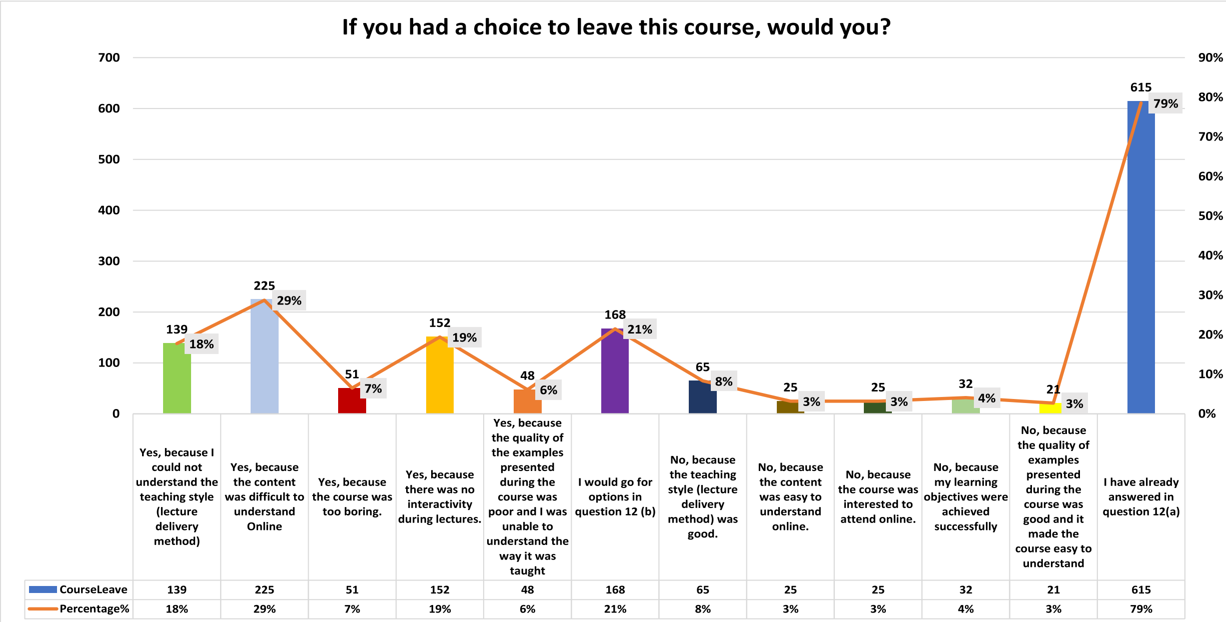

FIGURE 14. Percentage of students willingness to leave the . online course learning through LMS.

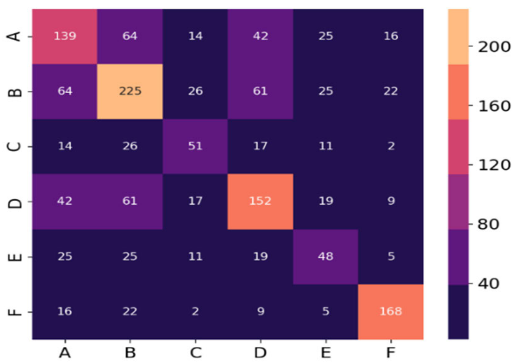

FIGURE 15. Confusion matrix about if the choice is given to leave the course.

online mood of learning. The choice of answer and their percentage of being selected together with the other options shows that option A *(the overall online learning experience was bad because of lack of face-to-face communication and less interaction made it difficult to learn through the online platform)* depicts the high concurrence with option C *(the overall online learning experience was bad because the content delivery is difficult to understand in an e-learning environment)*. The confusion matrix indicates that option C has the overall highest concurrence of appearing together with all the other options. Options F, G, H, and I are not selected together with another option and have zero co-occurrence.

3) RESEARCH FINDINGS AND RESULT INTERPRETATIONS

Based on the survey results and analysis, many issues have been identified from the learner's point of view. According to the results of the responses, it is concluded that the course structure is designed using a conventional educational system. Their learning goals and learning outcomes are not achieved due to the way courses are designed and presented to students/learners who are based on an instructor-centered approach and do not support a student-centered approach.

Other critical problems that were raised by the respondents from the survey results were that existing learning systems do not support the freedom to learn according to learners' needs and preferences and do not support the freedom to learn according to the learner's pace of learning. According to the detailed analysis, it is also found that interfaces of existing learning systems fail to facilitate the interaction of instructors with learners and vice versa. Learning management system interfaces are not designed to facilitate student-to-student or learner-to-learner interaction and no model exists that is designed to facilitate instructor-to-instructor interaction. Present systems interfaces lack support for teamwork, group learning, group activities, etc. The grading and assessment features in existing learning management systems are dearth to assist instructors and learners. Respondents also have highlighted the issue that learning material, supporting material, examples, etc. presented to the students during the course does not support user learning style.

B. EXPERIMENT-II: LABORATORY EXPERIMENT

One of the important techniques to collect primary data using a qualitative approach is observations and fieldwork Experiment -II is designed to evaluate the performance of two individual groups of students who have experienced learning in two extremely different environments that is face to face and online modes of learning by watching online lectures

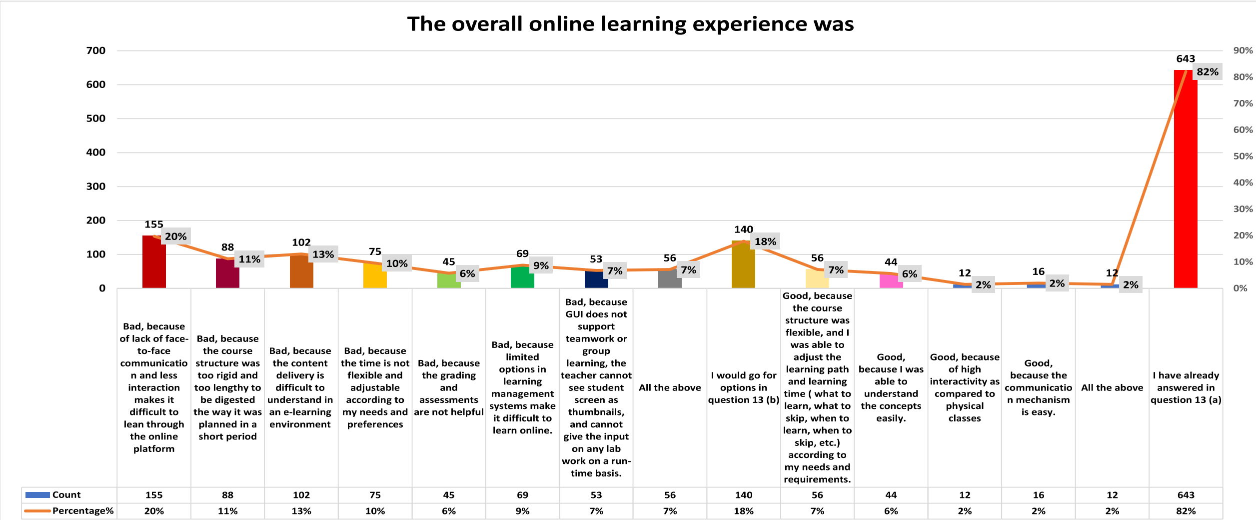

FIGURE 16. Percentage of overall online experience.

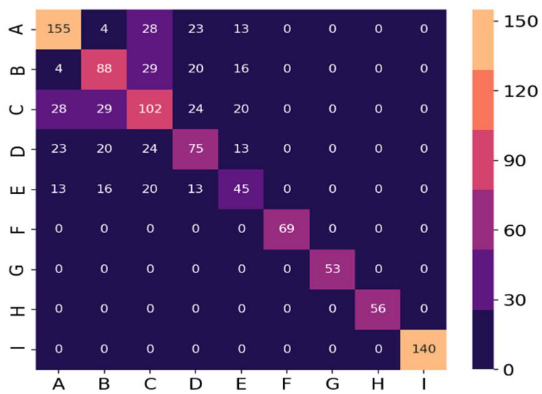

FIGURE 17. Confusion matrix of overall online learning experience.

and YouTube about practical labs through the conduct of laboratory environment. For this purpose, the Elevated Plus Maze (EPM) test is used to assess anxiety-related behavior in rodent models of CNS disorders. This test is also used to understand behavioral patterns and to screen for putative anxiolytic compounds. As subjects freely explore the maze, their behavior is recorded. The preference for being in open arms over closed arms (expressed either as a percentage of entries and/or a percentage of time spent in the open arms) is calculated to measure anxiety-like behavior. This test can be used to understand behavioral patterns and to screen for putative anxiolytic compounds.

The objective of this experiment was to compare the performance of those students who have learned using the online mode of learning by watching YouTube videos, or some other laboratory experiment videos and learning content provided by the instructors using existing learning management systems with those students who have practically experimented and learned to perform the tasks in a laboratory environment and who used face to face learning method for learning the theoretical contents where interaction with instructors and peers is comparatively easy and feedback of the instructor is timely and relevant. Both groups were asked to give an assessment and perform the experiment in a lab environment.

1) PARTICIPANTS DEMOGRAPHIC

Participants were university third-year students who were studying in the Bioscience department of a university. The experiment was designed to be conducted in a controlled lab environment between subjects. Each group was based on 15 participants with the same demographic history. Online Section: -Group A: Students who have performed lab experiments online through tutorial videos and the learning content provided to them using the existing learning management systems.

F2F Section-Group B: Students who have performed lab experiments physically in a lab environment.

2) DESIGN AND CONSTRAINTS

The EPM apparatus consists of a plus-shaped maze elevated above the floor with two oppositely positioned closed arms, two oppositely positioned open arms, and a center area. The test is based on two conflicting innate tendencies: exploring a novel environment and avoiding elevated and open spaces constituting situations of predator risk. As subjects freely explore the maze, their behavior is recorded. The preference for being in open arms over closed arms (expressed either as a percentage of entries and/or a percentage of time spent in the open arms) is calculated to measure anxiety-like behavior. Students were asked to observe the animal and note down the several below-mentioned parameters either through direct observation or through recorded videos.

i. Total time spent in open arms.
ii. Total time spent in the closed arm.

TABLE 5. Statistical analysis to compare the performance of two Groups.

Mean and Standard Deviation of Bioscience Department 3rd Year Semester Students of Pharmacology Course						
	Online Section-Group A (n = 15)			F2F Section-Group B (n = 15)		
Variables	Mean	SD	Std. Error Mean	Mean	SD	Std. Error Mean
Theoretical Question Points	μ=45.2	σ = 5.93	1.5	μ= 47.6	σ = 3.3	0.8
Performance based Assessment	μ= 14.6	σ =2.65	0.7	μ= 18.75	σ = 1.4	0.35

iii. No. of entry in open-arm
iv. Body stretched.
v. Head Dipping.

The experimenter will stand as far away as possible from the maze and out of sight of the test animal, outside of the room if necessary. Must avoid making unnecessary movements or sounds. According to research literature and proven results by our Experiment-I, a clear understanding is developed that students are more motivated towards learning and engaged with different class or lab activities in a traditional classroom environment. Due to the limitations and lack of interaction in existing learning management systems, instructors fail to involve students throughout in learning process and this decreases the student learning mechanism. This study examined the two modalities: *Face to Face and Online Learning* over the laboratory experiment based on animals' behavior testing.

The following research question is designed to see the difference in students' performance in conducting lab experiments if studied online or face to face.

RQ1: Are there any considerable differences in students' performance performing lab experiments for those who have learned online through YouTube videos or those who have learned face-to-face in a physical environment?

Table 5 below shows the statistical analysis to compare the performance of the two groups.

From Fig 18. above the group statistics, results show that average scores of Face-to-Face learning in performance-based assessments in a laboratory experiment (M = 18.75) differ significantly from that of the Online method of learning (M = 14.6). Thus, the level of achievement in performing practicals in a physical environment where interaction and collaboration with the lab equipment, with the peers, or the instruction taken directly from the instructors in the physical environment is considered important. Further, the average score for learning theoretical aspects using face to face learning method (M=47.6) varies considerably from that of the online method of learning where the mean is (M = 45.2). Fig 19. proves that Group A who has learned online has a high variance in both theoretical assessment and performance-based lab experiments. The variance of Group A in theoretical assessment ($\sigma = 5.93$) and performance-based experiment ($\sigma = 2.65$) noticeably varies from that of the face-to-face learning section ($\sigma = 3.3$) in theoretical assessments and ($\sigma = 1.4$) in a laboratory experiment. Group A who has learned to perform lab experiments and attempted theoretical questions by learning online using the content provided by instructors using existing learning management systems and by watching YouTube videos have poor performance in laboratory experiments and even have a low average in theoretical assessments. with Group B who had the experience of face-to-face learning. Therefore, the results show that e-learning material can provide the content and knowledge but how to use the knowledge in the practical environment is lacking due to the lack of learning management systems that do not support interaction with instructors or learners and do not facilitate collaboration.

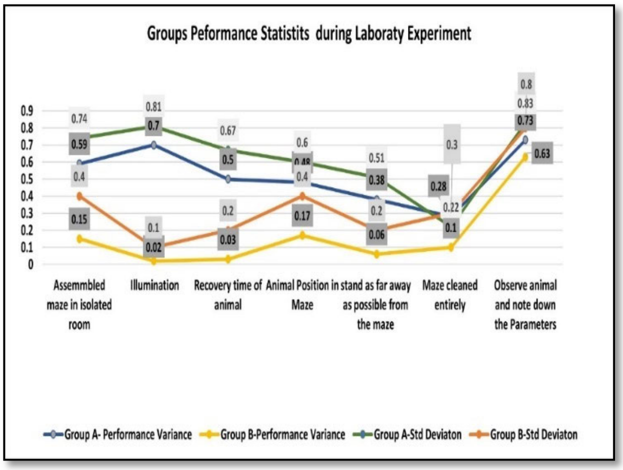

FIGURE 18. Group performance statistics of laboratory experiments in a controlled environment.

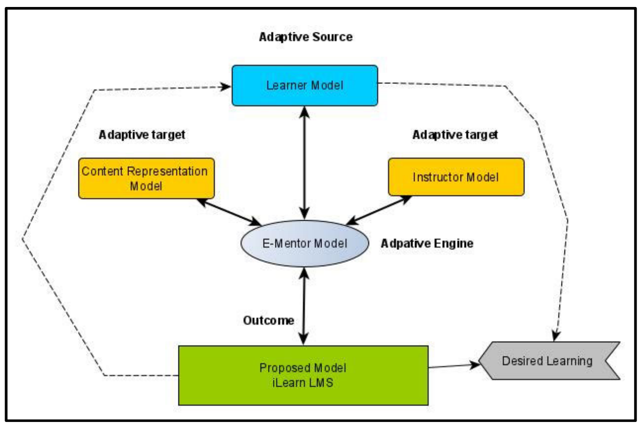

FIGURE 19. Proposed learning model.

3) OBSERVATION AND FINDINGS

According to Performance-wise results, Group A was more confused while handling the animal. The protocol followed during the experiment was not followed properly. Extraneous interference of noises and movement during the experiment disturbed the animal. It was observed that the lab door where the experiment was performed was left open by the student which increased the illumination in the room and created an anxiogenic effect. Further, the animals once moved from their cages to the lab room should be left for a minimum of 45 to 60 min to recover from the stress of being moved. The group started to observe the movements right after moving the animal due to which the animal behavior was recorded as stressed and most of the time the animals did not stretch their arms, nor open their arms.

Performance-wise, Group B had comparatively performed much better except few who are phobic to handling animals. Most of the students kept in mind the fine and sensitive details while performing the experiments, an exception is still there. However, in comparison to the previous batch, their learning and performance were much better as they were in continuous practice and performing their physical laboratory experiments. The protocols were properly followed. The movements were properly recorded and measured. To answer the theoretical assessments about the lab activities were performed between subjects. According to the results, the performance of Group B was better in both theoretical aspects and in lab experiments in comparison to Group A who have learned through existing learning management systems and by watching YouTube videos.

Key constraints of existing LMS identified during the study:

After the detailed analysis and evaluation extracted from the experiments results following eight hypotheses have been proved.

C1: Learning Management Systems primarily function as content management systems but fail to fully support learner-to-content interaction.

C2: Learning Management Systems fail to provide the freedom to learn according to learners' needs and preferences.

C3: Learning Management Systems fail to provide the freedom to learn according to learners' pace of learning.

C4: Learning Management Systems fail to provide instructor-to-instructor Interaction

C5: Learning Management Systems fail to provide the Learner -to-Learner Interaction

C6: Learning Management Systems fail to provide the instructor -to-Learner Interaction

C7: The existing learning management systems interface lacks support for teamwork, group learning, group activities, etc.

IV. PROPOSED MODEL

The above-mentioned research problem shall be addressed by developing a model that shall have the capabilities not to just provide personalized and goal-oriented education to the knowledge seekers but also to provide the e-mentoring capabilities by which they shall be guided properly. The following are the key components of the proposed model.

- *The learner Model* is meant to provide personalized and adaptive learning content to leaner. A learner model is designed that has all the pertinent information about leaner. It is an adaptive source.
- *The Instructor Model:* is meant to provide the platform to the instructors from any domain or knowledge area, where they can design the content according to their preferred teaching style. This model provides the communication and collaboration aspects that will help instructors to develop a course/content.
- *Learning Representation Model:* It is designed to provide personalized learning content to learners. This model has learning concepts that are associated with learning objects that provide learning resource sequences and generate a personalized learning path. It is an adaptive target that together will leaner model.
- *The E-Mentoring Model* is a software agent that has automated behavior. The e-mentoring model is meant to provide self-directed learning to learners through personalized learning paths. The e-mentor model will guide learners in their learning progress and content selection. It will engage and motivate the learner and will bring learning curiosity.
- *Adaptive Engine:* The adaptive engine will work like a navigation engine and recommendation engine. Initially, an adaptive navigation engine will decide which concept a learner will learn next based on the learner's needs and preferences. Second, the adaptive engine after choosing the concept will decide what learning material will best serve the need of a leaner. For instance, the next concept the engine will choose to show to the learner is 'Classes in Java' now the text task is to choose which author material to recommend and what the learning object like the material will be presented as a video as a text file, as a practical example, etc.

Fig 19. below is the block diagram for our proposed learning model. The learner model is an adaptive source whereas the content representation model and instructor model are adaptive targets [32].

A. LEARNER MODEL

A learner model is designed to store learners' information. It is a key component of any e-learning system to provide their adaptation according to the learner's goals and preferences, learner profile, learning style, knowledge, and performance. [32], [33].The proposed learner model stores learners' unique attributes to adapt learning materials. The learner profile includes the learner's biodata, learning objective learning style, and time to learn. It enables the system to deliver customized learning content/courses, based on the individual learner's, needs and preferences. Felder and Silverman's learning model is used to identify the learning style of a learner [34]. Felder-Silverman learning style shall be identified using the convention and automatic approach. Initially, learners' learning style is identified by using the Felder & Silverman Index of learning style (ILS) questionnaire. Learners shall be asked to fill out a questionnaire [35],

[36]. Later, the changes in the profile be maintained using the automatic approach to identify the changes in the learners' learning characteristics over time that shall dynamically update the profile [36]. Several studies have been found in the literature to automatically identify the learner style using different artificial intelligent classification techniques that include, Reinforcement learning [37] Fuzzy logic, Fuzzy C Means(FCM) algorithm [38], Decision trees techniques, Bayesian Networks techniques, Neural Network Techniques, [35] [39] Software Agents [40], [41] etc. Each technique's performance varies from one to another based on the choice of features, parameters, dataset size, etc. collected from the e-learning systems.

In Fig 20. the learner's learning style with the teacher's teaching style is mapped which will be used to provide personalized content to the learner and will also facilitate the learner to identify the learner's style before designing the course material.

FIGURE 20. Felder and Silverman's learning style model mapped with the instructor's teaching style.

The Felder and Silverman ILS instrument consists of 44 questions. 11 questions are designed for each of the four defined dimensions. For each of the four, the score provided as 11A, 9A, 7A, 5A, 3A, 1A, 1B,3B, 5B, 7B, 9B, or 11B where the letter "A" and letter "B" represent one pole of each dimension [39]. ILS scale range says that if the score lies between 1 to 4 the learner style is balanced on both dimensions of the scale. If the score lies between 5-7 then the learner can learn easily in that teaching environment which favors that dimension. If the score lies between 9 to 11 then the learner has a strong preference for one dimension and will face difficulty if the teaching environment will not favor the required dimension. The Felder and Silverman Learning style model is usually referred to as 8 learning styles that provide 16 different clusters of learning styles [35], [39], [42], [43]. The diagram below shows the combination of 4 learning styles each has two opposite dimensions. Fig 22 demonstrates the learning style cluster of the Felder and Silverman model.

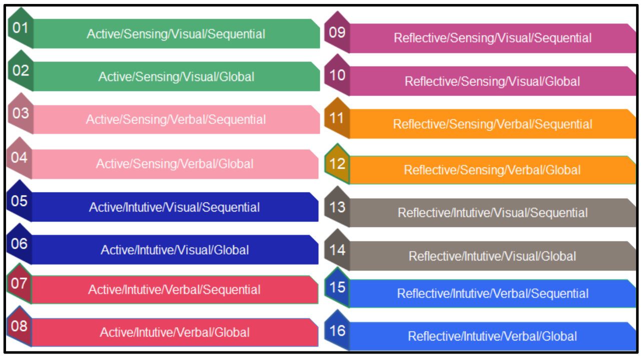

FIGURE 21. Felder&. Silverman learning style cluster.

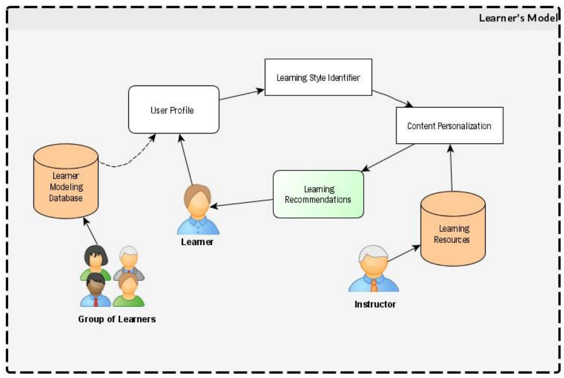

FIGURE 22. Learner's model.

The learning style dimension is categorized into 16 cluster combinations in the equation below.

Learning Styles Dimensions (LSDs) = {(A, S, Vi, Seq), (A, S, Vi, G), (A, S, Ve, Seq), (A, S, Ve, G), (A, I, Vi, Seq), (A, I, Vi, G), (A, I, Ve, Seq), (A, I, Ve, G), (R, S, Vi, Seq), (R, S, Vi, G), ((R, I, Ve, Seq), (R, S, Ve, G), (R, I, Vi, Seq), (R, I, Vi, G), (R, S, Ve, Seq), ((R, I, Ve, G)} (IV-D)

In Table 6 below, learning objects are identified with each learning style. The course material can be designed to keep the learning style of the learners. learning style association dictionary is created using these learning objects. This will help to identify the learning style of a learner.

To determine which of the four learning styles a learner may prefer, a set of 44 questions is presented to identify the learner's learning style. Each dimension of learning style has a total of 11 questions each of which has two options, option *a* and option *b*. The learner? preferred learning style is determined by the highest score a learner obtained and it is analyzed from the submitted questionnaire. The Algorithm is designed based on the Felder and Silverman proposed model [44]. The learning style questionnaire is categorized into four categories with each category representing one of the four learning dimensions. Each dimension comprises two

TABLE 6. Learning objects mapped with learning styles.

Learning Style	Learning Objects	Information Style/Dimension
Active	Problem-solving case studies, exercises, questions Experiments, Group activities, and group tasks Discussion groups (forum, blogs) and brainstorming sessions Question/Answers, Guessing exercises	*Processing*
Reflective	Case studies Presentations Research/literature review Summaries, reading material/books	
Sensing	Presentations, Problem-solving case studies/exercises/questions Reading material/facts/ explanations/examples Question/Answers, Guessing exercises The practical situation, Hands-on, Demos	*Perception*
Intuitive	Discussion groups (forum, blogs) Simulations Role Games, innovative task Theoretical study Case studies. Algorithms, Examples, Summaries	
Visual	Simulations/Demonstrations Pictorial representation and images/infographics Charts Video/Movies and Animations Diagrams/flowcharts	*Input*
Verbal	Reading material/ textual information Audio/ Podcasts Discussion groups/brainstorming sessions	
Sequential	Step-by-step exercising Presentations Books Construct link pages/ pre-defined road map	*Understanding*
Global	Brainstorming sessions, Case studies. Role games Summaries/ Abstracts/ Overview	

opposite categories, and each learner has a dominant preference in each dimension's type. The four dimensions include: (Active/Reflective), (Sensing/Intuitive), (Visual/Verbal) and (Sequential/Global). A learner's learning style is identified by combining one category from each dimension. Let's assume that the total number of selected questions a is X and b is Y, so for instance if the value of X = 8 and the value of Y = 5, the value for this dimension will be 3a. The smaller value is subtracted from the larger value and the letter of the larger value than an (X) is selected. The value in each dimension is normalized where 11a is equal to 1 and 11b is equal to 0 for convenient processing [44]. The table below shows the index of leaning style by Felder & Silverman.

Therefore,

$$\text{LSi di} \in [1, 0] = \{(\text{LS1, d1}), (\text{LS2, d2}), (\text{LS3, d3}), (\text{LS4, d4})\} \quad (1)$$

where,

LSi = Learning Style Dimension i.e. (4 dimensions)

di = Dimension value, i-e (0,1)

The learning dimensions are represented in the following five equations below.

$$\text{LS} = \sum\{\text{ACT, REF, SEN, INT, VIS, VER, SEQ, GLO}\} \quad (2)$$

For Active/Reflective

$$\text{LSDs} = [\text{ACT/REF}] = \sum\nolimits_{k=1}^{11} (a.b)\,[Xi = \{X1 + X5 + X9 + X13 + X17 + X21 + X25 + X29 + X33 + X37 + X41\}] \quad (3)$$

IF

$Xi = \left(\sum a > \sum b\right)$

SET {Y = (a-b)}

[ACT/REF] = (J. 'a')

Else

SET {Y = (b-a)}

[ACT/REF] = (J. 'b')

For Sensing/Intuitive

$$\text{LSDs} = [\text{SEN/INT}] = \sum\nolimits_{k=1}^{11} (a.b)\,[Xi = \{X2 + X6 + X10 + X14 + X18 + X22 + X26 + X30 + X34 + X38 + X42\}] \quad (4)$$

IF

$Xi = \left(\sum a > \sum b\right)$

SET {Y = (a-b)}

[SEN/INT] = (J. 'a')

Else

SET {Y = (b-a)}

[SEN/INT] = (J. 'b')

For Visual/Verbal

$$\text{LSDs} = [\text{VIS/VER}] = \sum\nolimits_{k=1}^{11} (a.b)\,[Xi = \{X3 + X7 + X11 + X15 + X19 + X23 + X27 + X31 + X35 + X39 + X43\}] \quad (5)$$

If

$Xi = \left(\sum a > \sum b\right)$

SET {Y = (a-b)}

[VIS/VER] = (J. 'a')

Else

SET {Y = (b- a)}

[VIS/VER] = (J. 'b')

For Sequential/Global

$$\text{LSDs} = [\text{SEQ/GLO}] = \sum\nolimits_{k=1}^{11} (a.b)\,.Xi = \{X4 + X8 + X12 + X16 + X20 + X24$$

$$+ X28 + X32 + X36 + X40 + X44\} \tag{6}$$

IF
$Xi = \left(\sum a > \sum b\right)$
SET {Y = (a- b)}
[SEQ/GLO] = (J. 'a')
Else
SET {Y= (b- a)}
[SEQ/GLO] = (J. 'b')

Explanation of Scores:

The table below shows the representation of scores according to the Felder & Soloman Index of Learning Style (ILS) questionnaire [34], [45].

Algorithm 1 Index Learning Style Generation Algorithm

```
Declare string l_sumA
Declare string l_sumB
 /*Check the value of the variable quesval. */
if quesval = 'a' then
   Set values inquescol, 1, 0, and inuserid
else
   Set values inquescol, 0, 1, and inuserid
end if
 /* Calculate the sum of ques_val_A and
 ques_val_B for specific ques_col values
 associated with the "Activist/Reflector"
 dimension. */
Calculate: Sum of ques_val_A and and
 ques_val_B
l_sumA: = Sum of ques_val_A
l_sumB: = Sum of ques_val_B
 for each dimension of "Sensing/Intuitive",
 Visual/Verbal" and "Sequential/Global" do
   /*Compare l_sumA and l_sumB. */
   if l_sumA > l_sumB then
      @l_diff: = l_sumA - l_sumB
      Update act_ref in the table
 tblindividualquestionnair for given userID,
      Append @l_diff with the character 'a'
   else
     @l_diff: = l_sumB - l_sumA
     Update act_ref in the table
 tblindividualquestionnair for given userID,
      Append @l_diff with the character 'b'
   end if
   Update vis_ver column
end for
end
```

Figure 22 above illustrates the flow of information and processes involved in the learner's model within a proposed e-learning system. It emphasizes the importance of understanding the learner's profile and learning style to tailor the learning experience and provide suitable recommendations

- User Profile: It represents the learner's profile information, including personal details, educational background, and any other relevant data.
- Learning Style Identifier: This component assesses the learner's preferred learning style, using Felder and Silverman learning model.
- Content Personalization: Using the learner's profile and learning style information, this component customizes the e-learning content to match the learner's preferences and needs.
- Learning Recommendations: This component provides personalized learning content to the learner, suggesting relevant courses, modules, or resources based on their profile and learning style.
- Learning Resources: Instructors provide learning content to the system based on the teacher's teaching style. Content could be in the form of text, audio, video, etc.

B. INSTRUCTOR MODEL

Instructors are the subject or topic area experts with the skills to deliver their knowledge to learners through various delivery modes and languages [46]. With research, it is found that teaching has two clear distinct issues or attributes. One attribute is the delivery of the content and the second is the organization of the content [47]. The instructor is supposed to know both aspects. He/she should be good at delivering and in the organization of material. It is proven from the literature study that the organization of the material is highly dependent upon what learners want [48]. The instructor could be excellent when it comes to delivery but if the organization of the material is quite poor then the learner may not be getting that excitement and it is the other way also. It is observed that instructors are also not able to know what learner preferences and expectations are, which results in the creation of courses that do not satisfy customer needs and do not fulfill learners' expectations. It is further found from the research that the organization or arrangement of the content is more important than the delivery of the content. The delivery can be augmented by technology and there are numerous works of literature available [49].

This research aims to provide a detailed model that will cater to the needs of the learner as well as the instructor and will meet their expectations by matching the requirements in terms of learning style, learning objective, time, and preferences. This model focuses on the instructor's space where multiple teachers can create learning material based on their teaching styles. The concept of collaboration and communication while designing the course will be another aspect of this model. In the proposed model the instructors will create courses as per their preference after evaluating their own skill sets and learner demands for certain topics and certain delivery modes and languages. The proposed model includes a course development engine. This course development engine contains a structured course template, to be used by the instructor or course creator. Each course will have its own desired learning outcomes, defined delivery modes, and assessment techniques, each of which will be recorded in a database. The database will be critical for the working of the framework as it will include all the parameters of all courses, which will be used by the framework to provide the learner with a clear view of each course and match the expectations of students with the features of the course [49]. Fig 23. below is the mapping of the leaner model with the instructor model.

C. LEARNING REPRESENTATION MODEL

The learning includes a system of delivery of a specific set of knowledge to one or multiple learners [50]. Learning the material may have multiple attributes, which are the key elements in the selection of representing a learning content [31] Learners usually match their preferences and learning objectives with characteristics of the topic before they can select to register in one. In the course model, the selection of the topic is based on the matching of its features and characteristics with the learning objectives, learning time, and learning style of students [32].

The proposed learning representation model is based on the concept's repository. The concept repository contains the topic that is directed toward a learning material. For example, the Java language has many concepts that define Java, for instance, classes, objects, data types, string handling, etc. are the concepts and it has a repository containing all those relevant and related concepts. Content learning style refers to an individual's preferred way of acquiring and understanding information. Concept Sequencing is defined as the step-by-step structure or sequence of the topic that defines the concepts that are usually defined by the instructors who follow the teacher-centered approach, pre-defined in the e-learning systems, or by the content writer/designers. The objective of the learning path sequence is to generate a personalized learning path based on learners' needs and that shall focus on a student-centered approach instead of a teacher-centered approach. Fig. 24 illustrates the content representation engine of our proposed model [44].

This learning representation model has a learning engine that suggests and adapts the learning material based on the concept the learner wishes to learn. The time they are required to learn the material, the suitable learning object to learn the material based upon the learner's style, and the learning goal or objective [44].

D. MENTORING MODEL

The right selection of courses by the student is key to his/her success in the course and the right career progression [51]. However, there is no proper mentoring available to the learner especially if he is using an online e-learning mode for his learning. It was observed that there is no comprehensive model exists that can resolve many issues that persist in e-learning [52].

The objective of e-mentoring in our proposed model is to simplify learning by facilitating and guiding the learner about what to study, and how to get motivated toward learning. E-mentoring model accelerates self-directed learning by providing personalized content to each learner. Learners possess diverse motivations, prior knowledge, personalities, emotions, and learning habits, all of which can significantly influence their educational process. Therefore, our e-mentoring model effectively presents tailored learning experiences to each learner, maintaining their motivation throughout the learning process. It also aids learners in enhancing their self-motivation and provides personalized guidance by automatically detecting weak knowledge points. Personalized learning with e-mentor guidance enables learners to easily achieve course goals, fostering increased motivation and commitment to the learning journey. Below are the key characteristics of our E-Mentoring Model

A mentoring agent works like a virtual teacher or mentor. It is designed with the following capabilities:

1. The e-mentoring agent will know its interpretations based on predefined skills, knowledge
2. The E-mentoring agent shall adapt itself as per the individual learner's needs and skills. For achieving such type of agent, an agent shall have the following characteristics:
    - Set Pace (per individual based on feedback),
    - Generate Concept Sequence (conditional state)
    - Adjusting Knowledge Graph (filter, rectify)
3. Repeat the entire process.

Fig 25 below depicts the workflow of the proposed mentoring agent.

- *User Input:*

The learner selects content or topic of interest. Based on the learner's choice his profile is collected, including age, gender, location, purpose of learning, learning style, time availability, and language preference.

- *Content Organization:*

Content is organized and d based on the selected topics/content. A knowledge graph is created, integrating information about entities and relationships. Reasoning techniques are applied to derive new knowledge from the knowledge graph.

- *Storyboard Generation:*

The learner's profile and selected topic of interest are used to generate storyboards (scripts, lectures, etc.) for the mentoring agent. Storyboards are designed to match the learner's preferences and objectives.

- *Feedback*:

Content generated by the mentoring agent is presented to the learner for the assessment. Based on the provided learning content by the system the learner provides feedback and reviews on the content.

- *Pace Setting:*

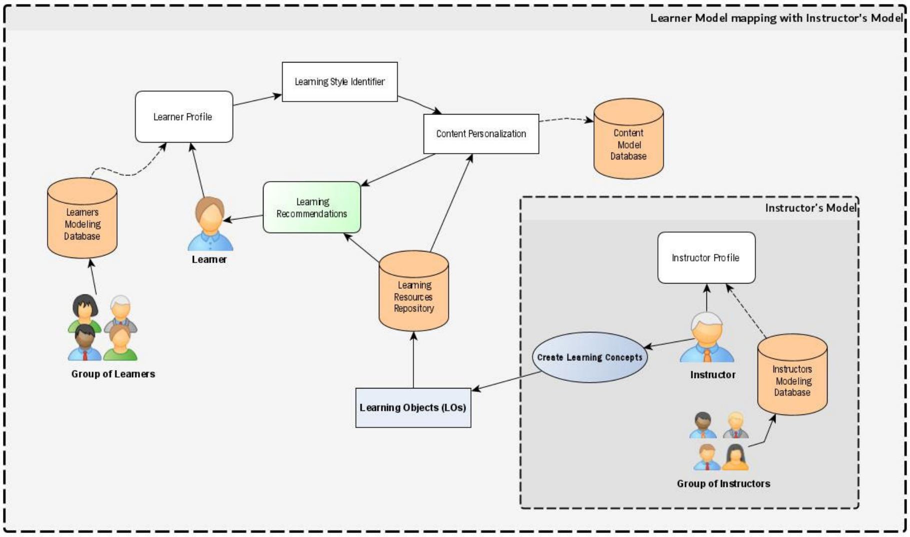

FIGURE 23. Learner model mapped with instructor model.

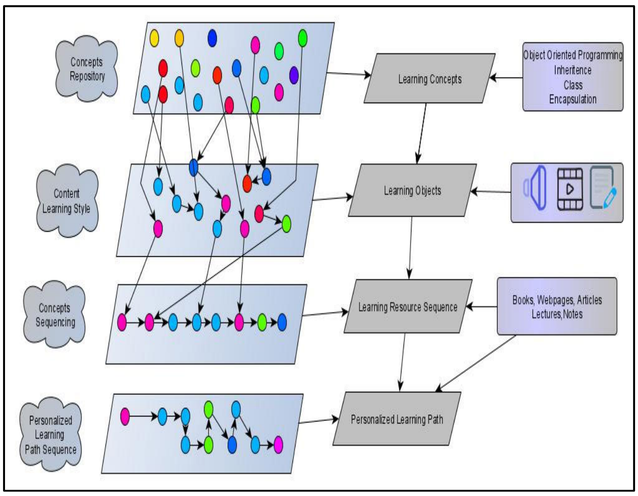

FIGURE 24. Learning representation model workflow.

The mentoring agent adjusts its pace based on the learner's preferences. Pace can be customized to match the learner's preferences and optimize their learning experience.

- *Instructor Profile Management:*

The model also manages the instructor's profile and attributes.

Instructors are categorized based on expertise, experience, and skillset. Content ranking is determined based on learner's reviews and feedback. Instructors are guided on course creation and delivery modes based on learners' expectations.

This model aims to personalize the learning experience by considering the learner's profile, preferences, and objectives. It leverages knowledge graphs, reasoning techniques, and adaptive pacing to provide tailored content and guidance. Additionally, it incorporates instructor profile management to ensure high-quality and relevant content delivery.

$$\mathrm{F}\,(LS, LOsAND\ Time) \tag{1.1}$$

Our proposed model for the mentoring agent can also be expressed by axioms mentioned in the following equations:

$$\begin{aligned} \mathrm{MM} < -\text{Learner's Profile}\,(&Age, Gender, Location, \\ &Purpose\ of\ Learning, Time\ to\ Learn, Language \\ &Preference, Learning\ Style \end{aligned} \tag{1.2}$$

$$\begin{aligned} \mathrm{MM} < -\text{Storyboard} < -&\text{Keywords (extract)}, \\ &\text{Purpose for Organization of KG} \end{aligned} \tag{1.3}$$

$$\text{Set Pace} < -F(\text{LS, LO, AND Time}) \tag{1.4}$$

V. ELMS PROTOTYPE DESIGN AND ANALYSIS

Fig 20 above illustrates the basic architecture of the system which is comprised of three main entities: Learner Instructor, and Content. The system shall keep a huge content repository to fulfill students' needs by developing a mature learning path for the students.

Based upon the results and findings of the two research experiments conducted and after the concrete hypothesis, a personalized goal-oriented learning system with e-mentoring capabilities is designed and evaluated that has tried to deal with the issues identified in existing e-learning systems.

A. LEARNER ROLES AND TASKS ASSOCIATED WITH THE SYSTEM

By using the proposed learning system, a learner shall be able to do the following tasks.

- Login/Sign up
- After successful signup learners fill out a questionnaire based on the learning style model proposed by Felder and Silverman.

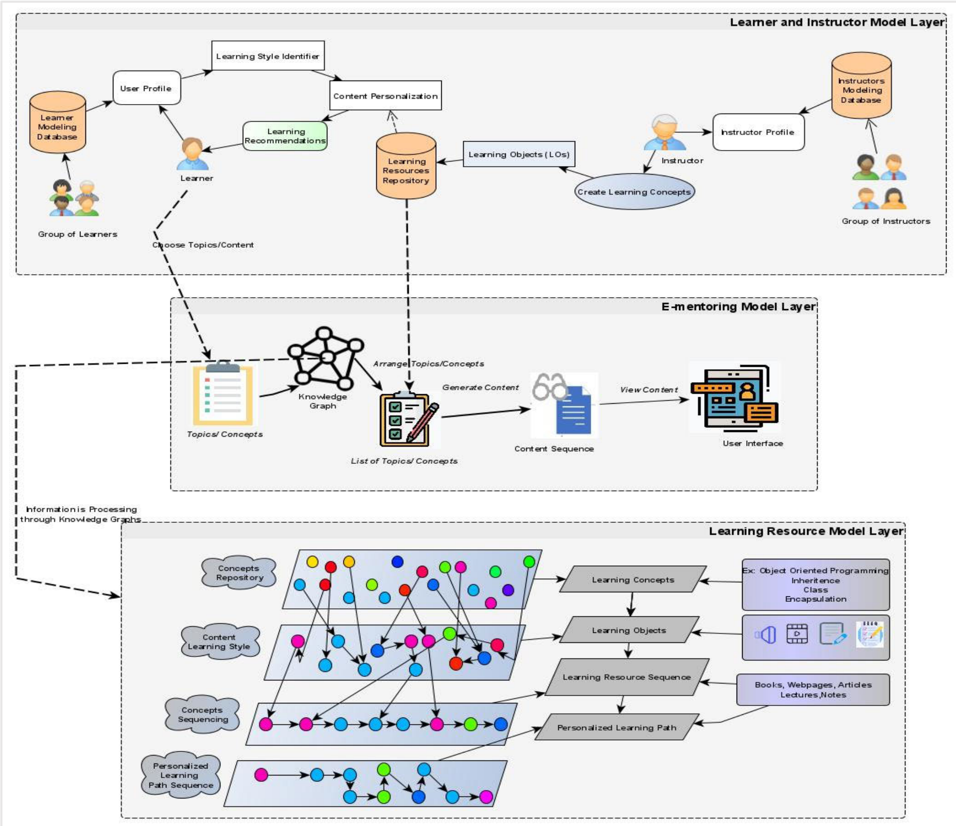

FIGURE 25. Model for an e-mentoring agent.

- The system calculates and identifies the learning style of the learner based on the answers submitted.
- A concise learning outcome form is displayed on the learner's screen which identifies the objective and time duration of learning content.
- The learning path is developed based on the learner's profile, learning style, and learning objectives identified.
- Learning material suggested by the system and learning path is designed.
- Leaner and view progress, manage course.
- Attempt assessments. Assessments will make the developed learning path more mature.

B. SYSTEM DESIGN'S PERSPECTIVES

The learning style of the learner is identified by implementing the Felder-Silverman learning model to calculate and generate an initial learning path that helps throughout the learning process. At the time of creating an account, the system will hold learners' data that will be used for profiling and save the student's current education level and degree/certification he/she attained. This information helps the system to present content to the student as per the dependency of content enrolled. Once a learner needs to register for a particular course/content he/she will be asked a couple of questions related to the goal he/she wants to achieve through the enrolled content. Eventually from all the information taken above by the system at different levels, a personalized learning path will be populated presenting the complete sequence of activities in a sorted manner. This sequence will be updated dynamically based on the student's performance throughout. Once a student watches/reads content he/she will be asked to put his or her feedback related to content and its tutor. This will help the system analyze what content is to be presented in the future and act more maturely. Afterward, the student needs to attempt an assessment and gather the overall performance that will help the system to promote the student to the next step or stay on the same by presenting different material.

The process will be followed throughout the learning process and the guided learning path will be changed accordingly stepwise.

1) CREATE ACCOUNT AND LOGIN

Students will create an account and fill out the required data to successfully sign up for the system. The system will save the user profile and its domain knowledge and use it for future purposes.

2) LEARNING STYLE BASED UPON FELDER AND SILVERMAN LEARNING MODEL

After successful signup, the user needs to fill out a questionnaire based on the Felder-Silverman Learning Model. The questionnaire takes the input-asked questions and, on its

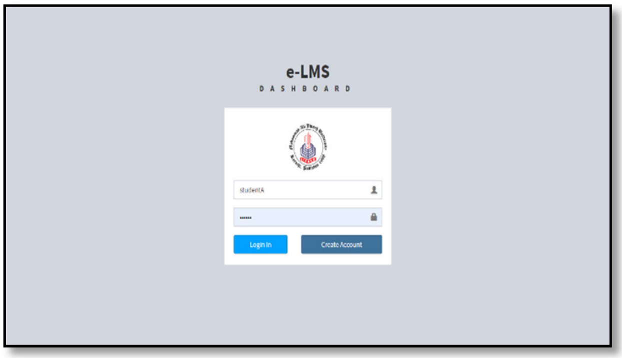

FIGURE 26. eLMS login page.

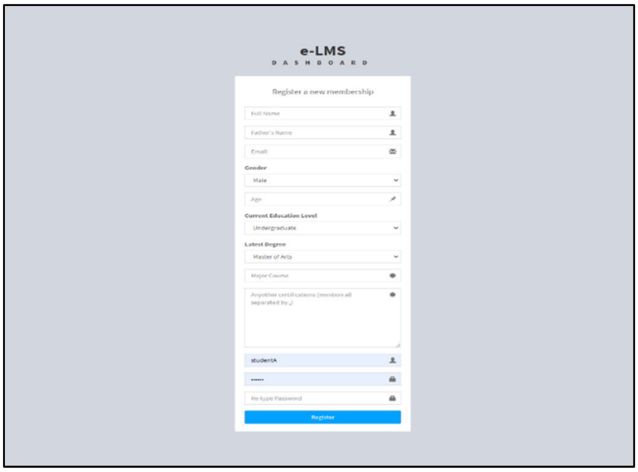

FIGURE 27. eLMS registration page.

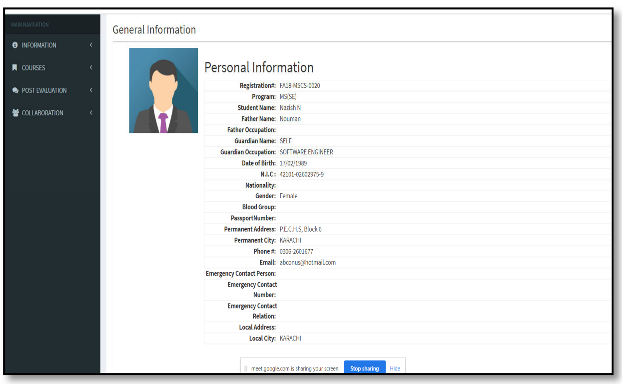

FIGURE 28. Learners dashboard.

basis, applies the implemented model and calculates the learning style of the individual.

3) COURSE/CONTENT REGISTRATION MODULE

Students can register for multiple courses he/she likes to learn. One can register for a complete course or the contents available and simply search on the page with the same criteria. At the time of enrolment, the system will ask the learner to fill out an objective feedback form analyzing the student's

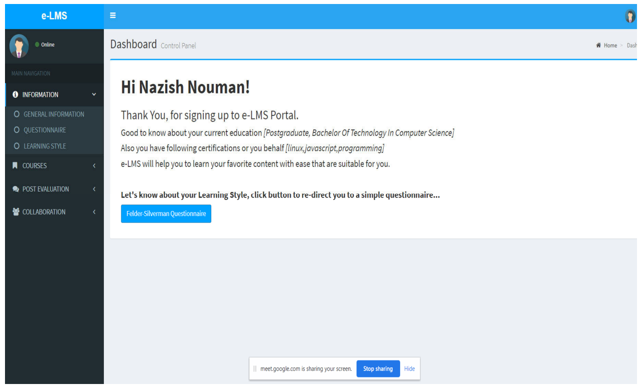

FIGURE 29. Felder &. Silverman-learning style model.

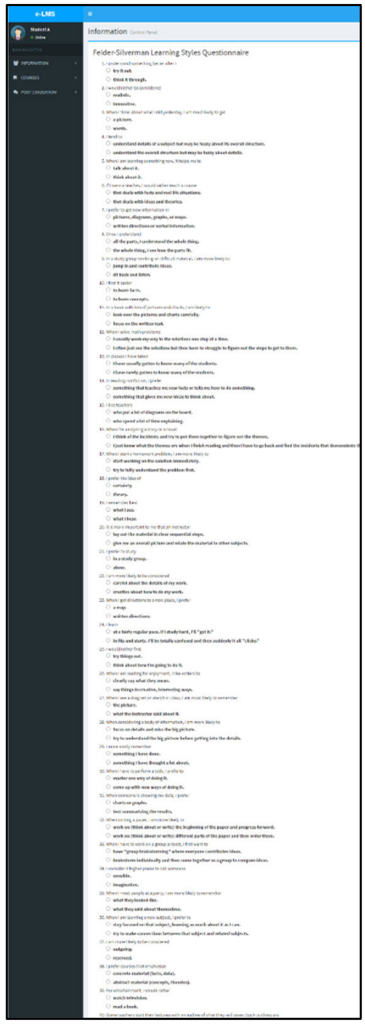

FIGURE 30. Questionnaire based-learning style model.

objective and to present content to achieve the required goal as mentioned in diagrams.

4) LEARNERS DASHBOARD TO VIEW REGISTERED COURSE/CONTENT

Once a user enrolls in a course, he/she can manage its courses/content and view the content for the registered

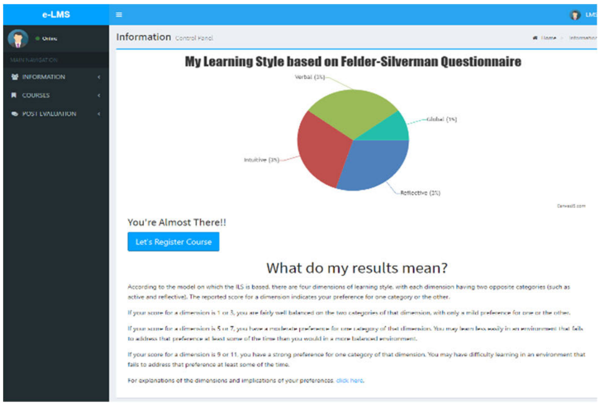

FIGURE 31. Graphical representation of learning styles identified.

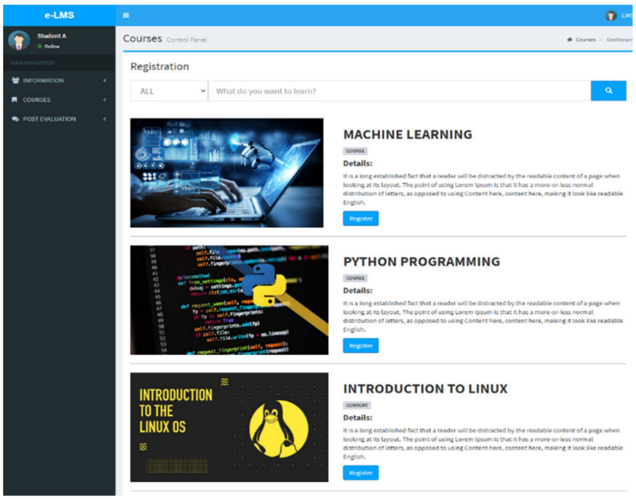

FIGURE 32. Course/content registration module.

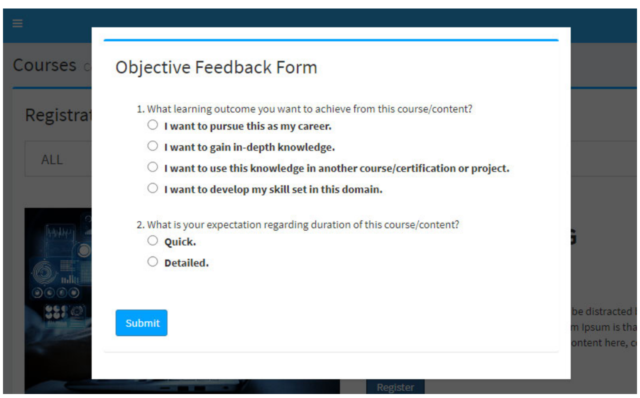

FIGURE 33. Learning outcome-based questions.

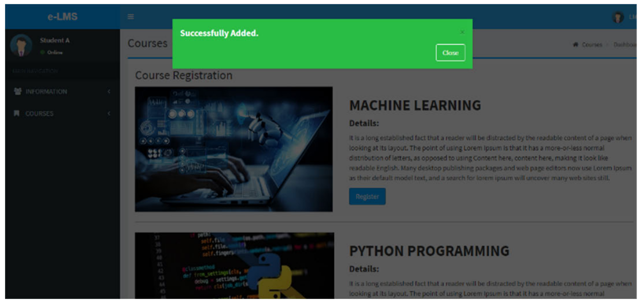

FIGURE 34. Course registered successfully.

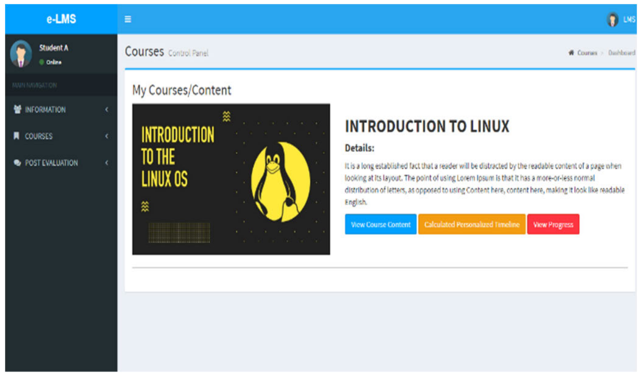

FIGURE 35. Learners dashboard to view registered course/content.

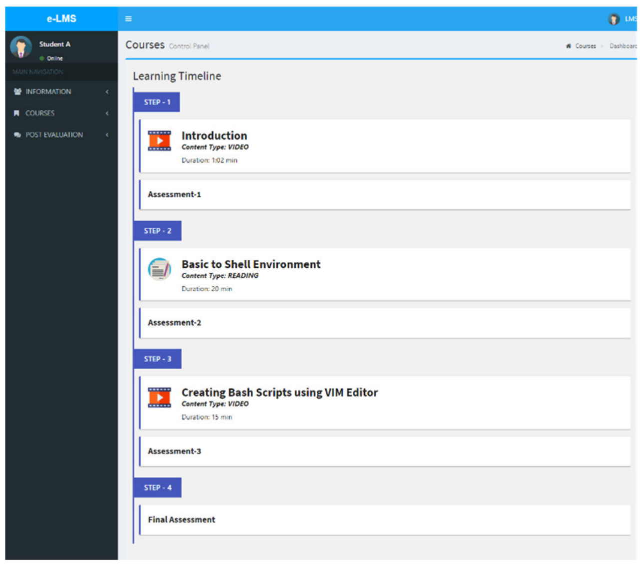

FIGURE 36. Suggested learning timeline.

courses, and the learning timeline/goal-oriented path that will be updated throughout the course.

Students can view the content available initially. Once the content has been watched a feedback form appears that needs to be filled requiring the feedback related to content recently watched. This will help the system to analyze the content presented and if required amendments in the learning path will be made.

5) LEARNERS' ASSESSMENT DESIGN BASED ON THE SUGGESTED CONTENT

Learners shall be guided to perform assessment tests by the end of learning content or course. This will help the system

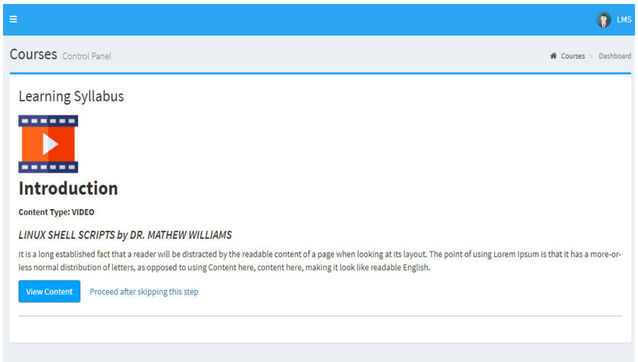

FIGURE 37. Recommended learning course according to the learning style of a learner.

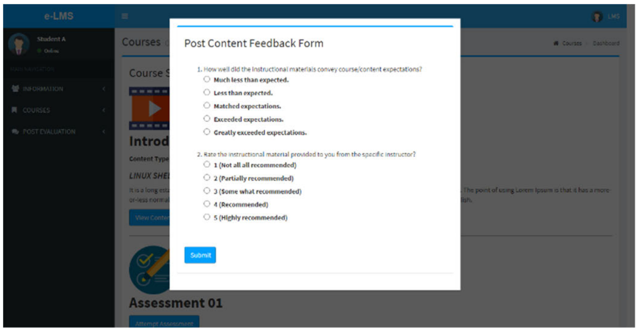

FIGURE 38. Suggested course/content post-evaluation feedback form.

dynamically update its knowledge base and update the learning style behavior at every step.

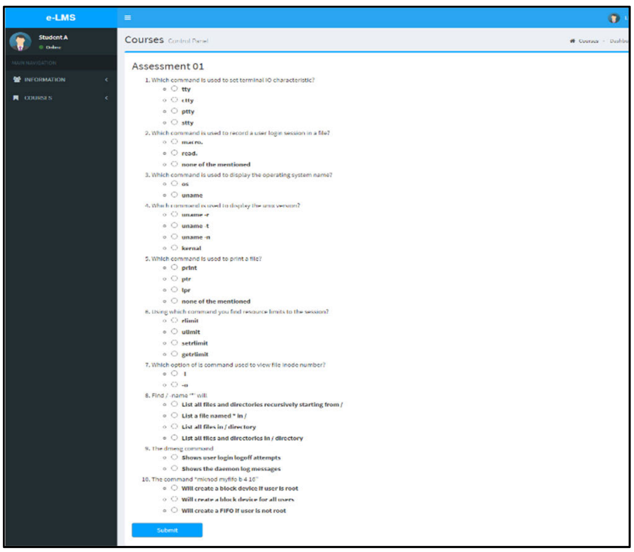

FIGURE 39. Learner's course assessment module.

6) SUGGESTED CONTENT BASED ON ASSESSMENT RESULTS

The system shall save the assessment results. Based on the feedback provided by the learner and the assessment result, the system shall decide the type and category of the content

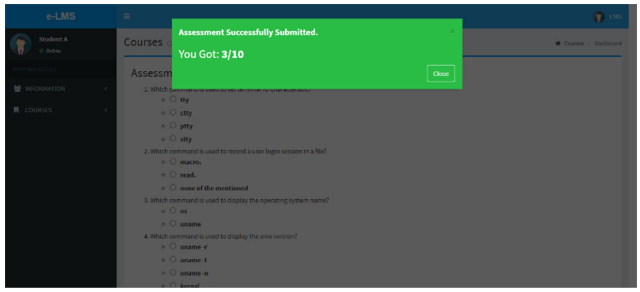

FIGURE 40. Learner's course assessment grading.

and will choose the content of the instructor/instructor presented to the learner accordingly.

7) POST EVALUATION MODULE

At the end of every course, the student needs to fill out a basic post-evaluation questionnaire that will help the system to have feedback on whether the course is helpful for the user or not and in case of any suggestions it might take it constructively. This feedback will help instructors to improve their teaching style and learning content.

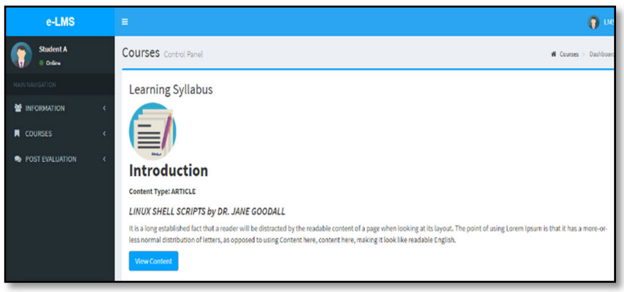

FIGURE 41. Suggested content based on learner's feedback.

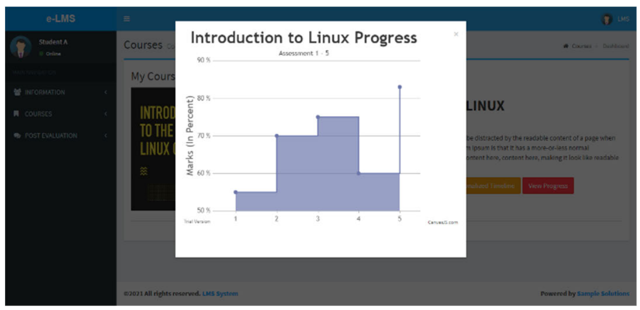

FIGURE 42. Progress graph based on learner's performance throughout the learning.

8) COLLABORATION AND INTERACTION MODULE

The diagrams below show the learners-to-learner and instructor-to-instructor interaction and collaboration modules. These modules are designed to keep the basic interaction and communication issues among learners and instructors

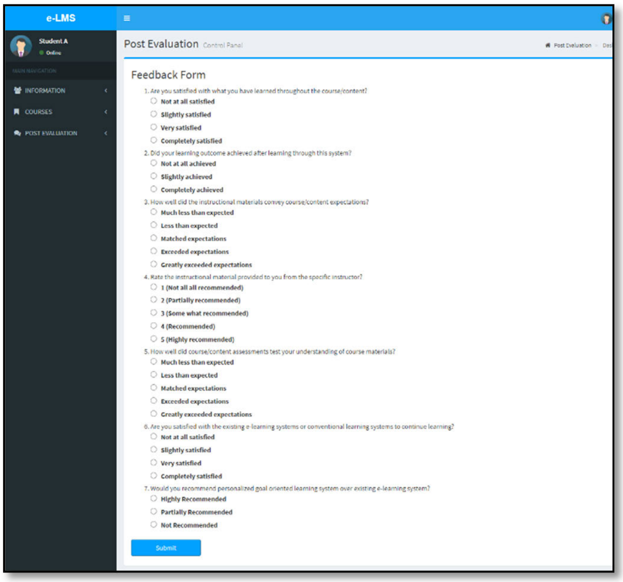

FIGURE 43. Leaner's post-evaluation form and feedback about learning content presented.

while using any eLearning platform or learning management system. With the help of the learner-learner interaction module, learners would be able to chat and discuss their assignments, and projects using the same LMS instead of using other apps or tools. This feature will also allow you to remotely access other's desktop screens in need of any assistance while learning. The purpose of introducing the instructor-to-instructor module in this system is to facilitate interaction and collaboration among instructors. By using these modules instructors may collaborate in designing a course and for collaborating.

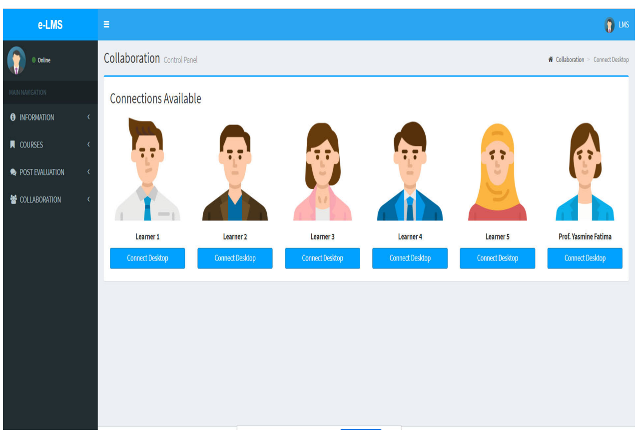

FIGURE 44. Leaner to learner interaction &. collaboration module through eLMS.

9) INSTRUCTOR COURSE DESIGN MODULE

Course Instructors can choose the course as per their choice and design it accordingly. They can choose the type of content that they want to prepare e.g.: quiz, teaching material, case study, video presentation, etc. They can also check the feedback received from the learner feedback form and can update their designed course content.

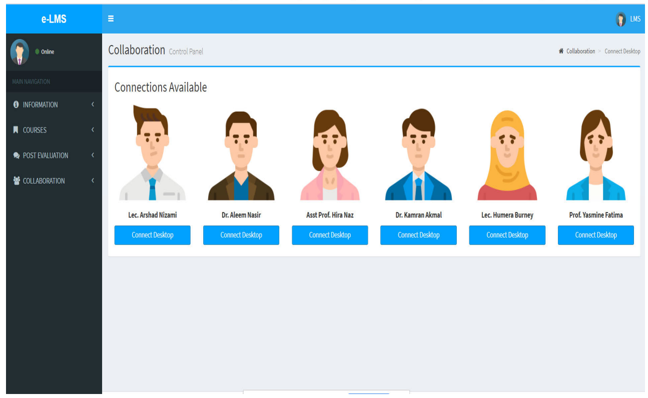

FIGURE 45. Instructor to instructor interaction &. collaboration module through eLMS.

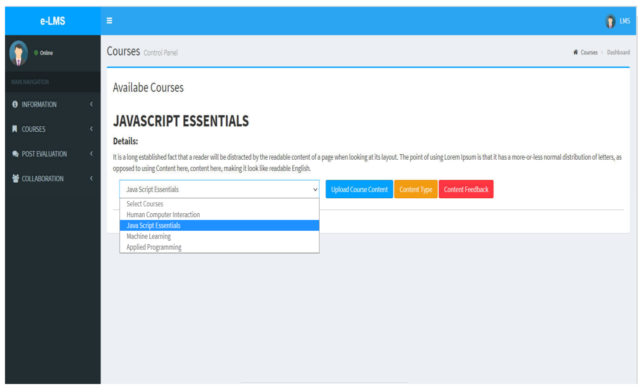

FIGURE 46. Instructor course design module.

C. COMPARISON OF THE PROPOSED MODEL'S FEATURES WITH THE EXISTING CONSTRAINTS.

In the table below, the features of the proposed learning model are presented. It is designed with consideration of the key constraints identified in the existing learning management systems.

D. EXPERIMENT III: PROTOTYPE TESTING AND EVALUATION

Experiment-III is designed to evaluate the proposed system by the actual users. To serve the purpose the evaluation is done in two phases. Pre-survey and post-survey evaluation with the university-level students who have background knowledge in computer science subjects.

1) EXPERIMENT OBJECTIVE AND METHODOLOGY

The objective of this experiment is to compare the performance of the two groups. Those students who have learned

TABLE 7. Felder & Silverman index of learning styles.

Active		Sensing		Visual		Sequential	
Reflective		Intuitive		Verbal		Global	
←a	b →	←a	b →	←a	b →	←a	b →
1		2		3		4	
5		6		7		8	
9		10		11		12	
13		14		15		16	
17		18		19		20	
21		22		23		24	
25		26		27		28	
29		30		31		32	
33		34		35		36	
37		38		39		40	
41		42		43		44	

TABLE 8. Felder & Silverman ILS representation.

ILS Scale Range	Representation according to Learner Style
1-3	Fairly balanced on both dimensions of scale
5-7	Moderately Preference for one dimension and will learn better what favors this dimension
9-11	Strong preference for one dimension and may face difficulty if that learning preference is not provided

a course through a conventional learning system with those students who were asked to use personalized goal-oriented eLMS. The experiment was conducted between subjects. For this purpose, 200 participants were divided into two groups A and B of 100 each. The pre-usability evaluation of systems was conducted between two individual groups. Participants of Group A were those students who were asked to continue their learning using currently available learning management systems while Group B was the experiment group, and they were suggested to learn from the personalized goal-oriented e-learning management system. Both the groups were independent t, and the results were satisfying.

2) PARTICIPANTS DEMOGRAPHICS

Demographics of Groups A and B are presented in the tables below. Individuals from age brackets 17-27, 28-37, and 38-47, education level Undergraduate, Graduate and Post-Graduate, and gender Male/Female were chosen for the experiment. Table 7. shows the demographics of those students who have learned through conventional learning management systems. Table 8. presents the count of students who were given access to e-LMS and have learned through the newly designed model.

TABLE 9. Features of the proposed learning model.

No.	*Key Constraints of Existing System*	*Features of the proposed Learning Model that addresses the existing constraints*
C1	Learning Management Systems primarily function as content management systems but fail to fully support learner-to-content interaction.	The proposed model enhances the interaction between the learner and the content by understanding the learner's style of learning and displaying the content accordingly.
C2	Learning Management Systems fail to provide the freedom to learn according to learners' needs and preferences.	One of the features of our proposed model is to identify the learning style of a learner. It is identified through a questionnaire form based on Felder and Silverman's learning style mode. This feature helps to understand learner preferences, learning objectives, and learning requirements.
C3	Learning Management Systems fail to provide the freedom to learn according to learners' pace of learning.	The proposed model provides flexibility in learning with an objective feedback form designed to understand the learner's pace in achieving their learning objectives within the required time.
C4	Learning Management Systems fail to provide instructor-to-instructor Interaction	The proposed model introduces the instructors to instructor collaboration and communication modules. It is facilitated by the chat feature. Through this feature instructors discuss and share ideas while designing learning content.
C5	Learning Management Systems fail to provide the Learner -to-Learner Interaction	The proposed model provides a chat feature by which learners can chat and discuss their assignments, and projects using the same LMS instead of using other apps or tools. This feature focuses on collaboration and information sharing among learners.
C6	Learning Management Systems fail to provide the Instructor -to-Learner Interaction	The proposed model enhances the instructor-learner interaction in which instructors get feedback on their provided learning material from learners.
C7	Existing learning management systems interfaces lack support for teamwork, group learning, group activities, etc.	The proposed model allows the learners to remotely access other's desktop screens in need of any assistance and for performing learning activities together like group tasks, and teamwork, The model focuses on information sharing and collaboration among learners.

3) RESULTS AND DISCUSSIONS

The quantitative survey questionnaire was designed to compare the expectations and satisfaction levels of two individual groups after learning through the provided learning management system. Participants of each group were inquired about their satisfaction level with learning the course/content after using the learning management systems. Group B that was given newly designed e-LMS tends to be more satisfied with what they have learned throughout the course/content than

TABLE 10. Demographic of Group-A participants.

Current Education Level	Age	Gender	Count of Current Education Level
Graduate	17-27	Female	15
Graduate	17-27	Male	15
Graduate	28-37	Male	20
Graduate	38-47	Male	15
Postgraduate	28-37	Male	10
Postgraduate	28-37	Female	10
Undergraduate	17-27	Female	15

TABLE 11. Demographic of Group-B participants.

Current Education Level	Age	Gender	Count of Current Education Level
Graduate	17-27	Female	10
Graduate	28-37	Female	10
Graduate	28-37	Male	15
Graduate	38-47	Female	15
Postgraduate	28-37	Male	10
Postgraduate	28-37	Male	15
Postgraduate	38-47	Female	10
Undergraduate	17-27	Male	15

the ones that learned using the conventional learning system. 40% of participants in Group A were not all satisfied with the existing learning system. 53% of participants in Group B were highly satisfied with the newly designed personalized e-learning system as shown in the figure below.

Students were further asked how many learning outcomes they were able to achieve using the provided systems as shown in Fig 48. According to the response of 25% of participants of Group A their learning outcomes are highly achieved. On the other hand, participants of Group B were highly satisfied with the system and according to responses received 50% of respondents who learned through the new elms answered that their learning outcomes were completely achieved and only 20% of participants of Group B responded that their learning outcomes are not achieved

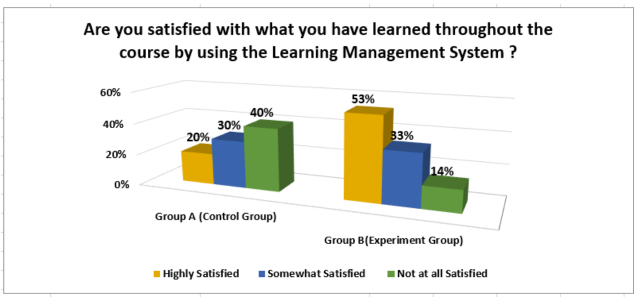

FIGURE 47. Group satisfaction measure after using the proposed LMS.

Participants of each group were asked to rate the level of expectations achieved from the provided instructional material to learn the course or content as depicted in Fig 49. None of the participants of Group A has responded that the expectations from the provided learning material are greatly exceeded. In contrast, 23% of the participants of Group B claimed that their expectations from the provided learning material to learn the content is greatly exceeded. 65% of the participants in Group A were highly dissatisfied with the conventional learning material and according to them, their expectations were not met. In contrast, only 19% of the participants in Group B assumed that their expectations were not matched by the provided instructional material as shown in the figure below.

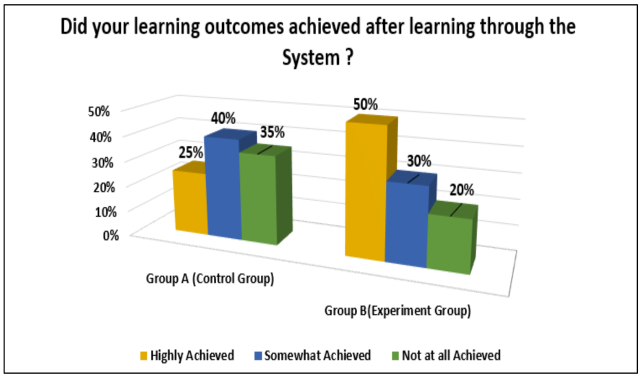

FIGURE 48. Measuring learning outcomes after learning through the proposed LMS.

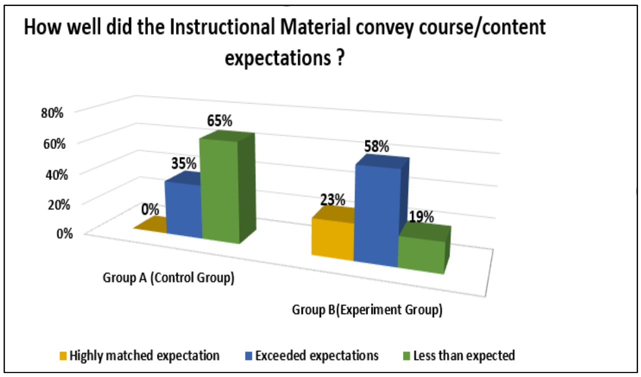

FIGURE 49. Expectations from the provided Instructional Material.

Participants of each group were asked to rate the instructional material provided to them as illustrated in Fig 50. Group B seems to be very satisfied with the new system. 23% of the respondents answered that they highly recommend the provided learning material. 47% of the participants recommend the provided material and only 12% said that they don't recommend the provided learning materials. In contracts, participants of Group A, who were asked to learn through a conventional learning system were not satisfied with the learning material. Only 10% answered that they highly recommend the learning material. 35% of the participants have partially recommended the learning material provided to them. Only 10% of the participants answered that they recommend it, and 27% of participants of Group A said they do not recommend it.

Each of the groups is asked to rate the assessment material provided to the learners to test their understanding of the

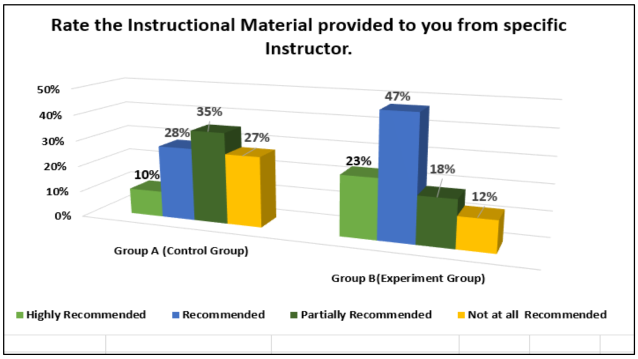

FIGURE 50. Rating for the instructional material.

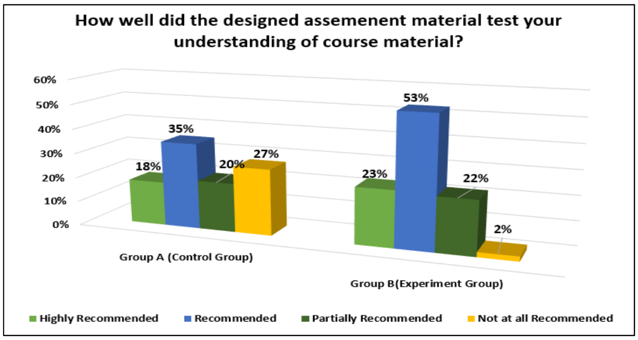

FIGURE 51. Assessment Feedback.

course material. Results are shown in Fig 51 below that the participant of Group B is satisfied with the provided assessment material that was used to test their understanding of the course material provided to them. According to Group B results, 2% of the participants were dissatisfied with the assessment material. 23% have highly recommended the assessment material, 53% have recommended and 22% have partially recommended it. Results of the participants in Group A have shown that the students are not very satisfied with the provided assessment material that was used to test their understanding of the course material provided to them. 27% of the participants said that they would not recommend the assessment material. 18% have highly recommended the material. 20% of the participants have partially recommended the assessment material and 35% have recommended the material.

Participant of each group is asked about the overall experience and satisfaction level that is achieved by learning through the traditional learning system as illustrated in Fig 52. Results have shown that both groups are not satisfied with the existing learning management systems and are reluctant to learn through the conventional learning style. Only 12% of the participants of Group A answered that they were completely satisfied with the existing system 21% of the participants claimed that they were partially satisfied with the existing learning model and according to 67% of the participants, they are not at all satisfied and do not wish to continue learning with the existing learning systems. According to the Group B results 68% were highly dissatisfied with the traditional learning system. Only 8% were highly satisfied and 24% were partially satisfied with the system.

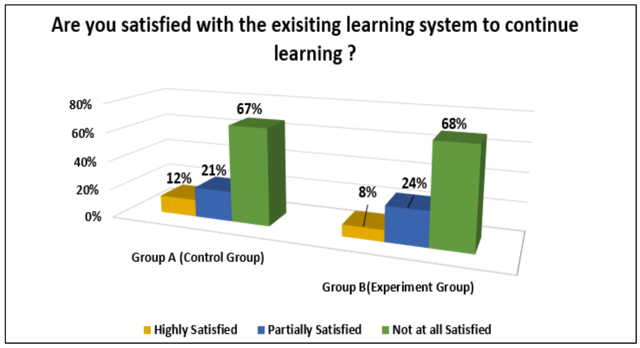

FIGURE 52. Measuring the satisfaction level of existing LMS.

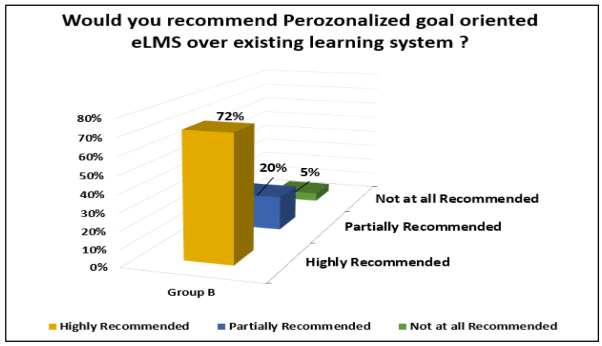

FIGURE 53. Feedback on the newly designed personalized eLMS.

Group B who was the experiment group and was given a new elms system for the pre-evaluation purpose were asked to provide feedback on the personalized goal-oriented learning system over the existing e-learning system. Participants of Group B were highly satisfied with the new eLMS because their learning outcomes and goals were achieved due to learning from the new system as illustrated in the figure below.

According to the participants they wish to continue learning through this system and will highly recommend it to others as well. Contrary to this Group A who used the conventional systems was unwilling to learn through the conventional learning system and were not satisfied with the existing learning management systems.

VI. CONCLUSION

After the comprehensive experiment design and detailed results analysis, it has been observed that the existing learning management systems have limited capabilities and fail to provide a personalized learning experience. It has been observed and concluded substantially with collective data, both qualitative and quantitative that currently available online learning management systems need to add necessities that the current situation demands to facilitate both instructors and learners to have a meaningful outcome from the selected learning material. The proposed system shows that the need for such learning management systems or eLearning systems is extremely important in the upcoming years.

This research lays down the foundation of an e-mentoring-based learning management system that takes on the student's student-centric approach. An e-mentor model is implemented that can provide supervised guidance. The model guides and suggests to the learner what to learn, and how to learn, design, and suggesting content that focuses on the learner's learning style, according to their needs and preferences is much more important and challenging. Results further show that the personalized goal-oriented system with e-mentoring capabilities can overcome the lack and requirements of the existing learning management systems and could replace the conventional learning style that is based on a teacher-centered approach. The results of the experiments conducted with the proposed system show that the behavior of the students toward the learning tasks, learning content, and their characterization truly relates to the content presented to the students based on their previous knowledge of the domain/course.

The proposed learning model with its e-mentoring capability has laid down the foundations for personalized learning. The proposed model can be enhanced in many ways. Deep learning models can be used to provide a personalized user experience. Keeping in view the growing privacy concerns, a privacy protection module can also be incorporated. We believe that the proposed learning model will not only improve the quality of learning but also provide an enjoyable learning experience to the users.

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