Adaptive Learning Systems based on ILOs of Courses

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Abstract - Nowadays, the use of e-learning techniques and methods is a very important challenge due to the importance of digital transformation to all countries. Firstly, the spread of the COVID-19 virus all over the world. Secondly, all students need to study their courses remotely from home to reduce the communication with others to save their life. All teachers need to engage their students effectively to study an online course, get more knowledge and high results at the end of these courses. Data mining is the best tool used to find a hidden pattern. We used an educational data mining tool to help teachers find the pros and cons of using an e-learning course with their students. We need to classify students on these online courses according to their ability to understand materials and quizzes, or assessment methods of the course, by making adaptive e-learning courses. In this paper, we will show the importance of using adaptive e-learning courses and the challenges faced by authors to build these systems, and we will list the different methods used with adaptive learning like gamification, brain-hex models, facial emotions, and we will also list a survey about other authors' techniques and methods used to find the student's learner style. We build a new proposed model of ILOs(Intended Learning Outcomes) adaptive learning with the emotion-based system to let the system find the student's learning style and build the material according to their skills and knowledge outcomes from the course and engage the use of facial emotion while taking the quiz to predict the student's results and the topics he/she needs to study more via our system to achieve high grades and knowledge. Our system finds that the visual students have the highest grades with 75%, followed by kinesthetic with 70% and the lowest grades in auditory with 50%.

Keywords- e-learning; education data mining; classification; gamification courses, Brain-hex model, facial emotions, Intended Learning Outcomes (ILOs).

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1 Introduction

Data mining, [1], is a process of analyzing large students' data and finding hidden patterns and knowledge that can be utilized to help in learning systems. It uses different classification techniques on the student's data and tracks their behavior while using the adaptive learning system.

Educational data mining is an important discipline to help the improvement of education systems by predicting students' behavior towards the online system. Today, educational institutions collect and archive massive amounts of data like registration data for every semester; attendance; total classwork; section grades; and final exam results to calculate the final GPA.

There are a lot of data mining techniques, [2], used in adaptive learning, like Naive Bayes Algorithm, Linear and Logistic Regression, machine learning techniques such as supervised learning (Support Vector Machine (SVM) and decision tree (DT)), and unsupervised learning (Clustering in Fuzzy Logic), artificial neural network (ANN), association rule mining, etc.

Teachers and instructors control their students in the traditional classroom by tracking their attitudes and facial emotions or reactions to the material. This allows the teacher to know if the students understand the material, he discusses with them. Also, traditional e-learning systems were uploading PowerPoint material to the students without any tracking of their learning styles. The number of students registered in courses is increasing every day, [3], [4]. We need to make predictions for students' behavior online and analyze this huge amount of information.

Today, the E-learning system, [5], increases the engagement of students by building an adaptive learning system to track the student's behavior and learning progress via new systems like the live classroom and Moodle websites in universities or schools. It will be more helpful to get the best final exam course grades at the end of the semester.

An adaptive e-learning system, [6], [7], gives the students opportunities to select which type of learning material they need to study according to their profile, interests, and previous knowledge of this course. The adaptive learning systems change the traditional methods like uploading presentation materials only to all students and let instructors track students' activity through the log data.

An adaptive e-learning system, [6], [8], [9], builds a classifier model to group students according to the learner style like the VAK model (Visual learners—Auditory learners—Kinesthetic learners) and Felder and Silverman Learning Style Model (FLSM), etc.

This paper is organized as follows In Section 2 we will discuss the data mining techniques used in education. In Section 3 we will show the importance of adaptive e-learning and the challenges facing the authors in building their models, and the more important classifier brain hex model used by the authors to find their learner style. In Section 4 we will list how authors use games to build adaptive gamification learning systems, Section 5 lists a lot of related work papers about adaptive learning and techniques used and lists the number of students engaged in every experiment; Section 6 describes how authors used facial emotions with adaptive learning systems; Section 7 describes our new proposed system ILOs adaptive learning with the emotion-based system, Section 8 discuss our experimental results and finally, the conclusion and future work.

2 Data Mining In Education

Data mining in education comes from different sources like machine learning, information visualization psychometrics, and other areas of computational modeling and statistics

Education mining techniques are divided into three parts: statistics, visualization, and web mining.

We must classify students' data and e-learning material using the following steps, [1]:

1) We need to identify the relationship between what we will store in the database and the information we collect from the students. To find the relationships between students, we will use different algorithms to predict the learner style by using classification, regression, and density estimation.

2) Clustering: we will create a group of students with the same behavior in the system based on their activity and learner style.

3) Relationship mining: to find the relationships between students, we predict the student's learning styles to improve their knowledge in this course and make changes in the teaching process methods and interactive materials.We can use one of the following techniques: association rule mining , Correlation mining , Causal DM and Sequential pattern mining.

4) Distillation of data for human judgment: it aims to make educational data understandable and help the human brain find new knowledge by presenting the data in different ways and using a lot of visualization methods.

5) Discovery with models.

Instructors are responsible for creating the presentations, pdf files, assignments, videos, quizzes, etc. that discuss the material to all students with different learner styles. Figure 1 shows the steps between the lectures and students while they interact and communicate with the classrooms and e-learning systems. The use of data mining techniques with education will improve the educational process and the engagement of the students and adaptive systems for different types of learners will get a good understanding of the course.

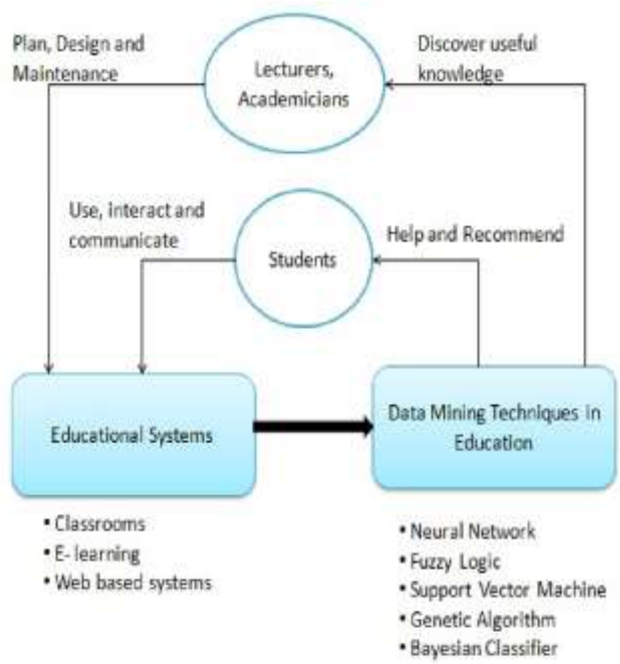

Fig. 1. Data mining techniques for students and lecturers, [1].

We have two types of data used in adaptive educational systems, [6]:

- *Structured data: personal data, learning management system, and performance evaluation data. Figure 2 shows the user data information.*
- *Unstructured data: Web data, social networking data, audio files, and learning video data.*

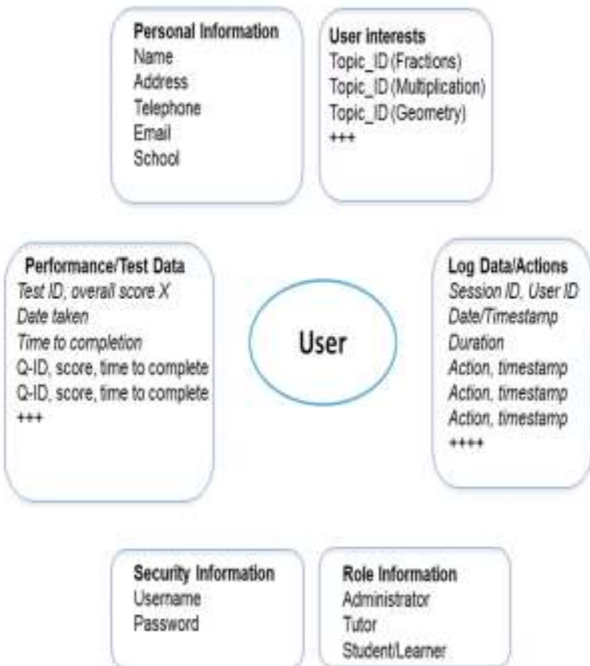

Fig. 2. User data information (structured data).

3 Adaptive Learning

Adaptive learning refers to building a model aiming to extract useful information from an online system adapted based on the student's activity on it.

3.1 Adaptive Learning Importance in Education

The important question we must ask before we start building an adaptive e-learning system:

1) *What? kind of data collected from the system while the students start learning on it.*

2) *Who? We need to know the ages of the students. We will build the system for them and know some of their characteristics.*

3) *How? Adaptive systems analyze this collected data and the method used to classify students according to their interests.*

4) *A success target. We will achieve success when our students achieve high scores via the new system compared with traditional classrooms.*

The e-learning data sources are:

- *The log data records and activity describe the student's interaction with the system and training materials.*
- *The performance records measure the student's results in passing the evaluation tests.*
- *The student's profile information will be used to classify students and the way they learn from the online system.*

There are two analytics types for adaptive e-learning:

- *Descriptive: it's provided past context and enables decisions that may influence next learning processes.*
- *Predictive: Make educated guesses about aspects and variables that may have an impact on current learning processes. That will enable teachers to take good actions about the next content that will appear to students.*

The adaptive learning system process as in Figure 3 starts by using the machine learning part to detect the learning path based on the learner's requirements and needs. The learning path is based on the previous user's interaction with the system and which ones are similar enough in characteristics to recommend the same learning style.

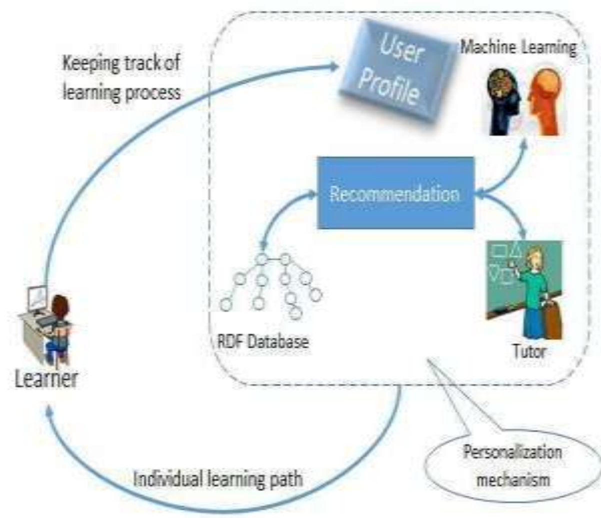

Fig 3: Adaptive E-learning System Architecture.

The Resource Description Framework is used with machine learning to extract the database about the learner's profile data and his log data on the system during the learning process and the time online on the system.

While we track his behavior on the system to adapt it and recommend a specific material that outcome from the machine learning interferences with the system.

In the adapted system, we need to store static and dynamic information about the student's profile and collect the learning and assessment process on the system.

The final target we need to achieve from the adaptive e-learning systems in the education process is that we need to measure student performance after the end of the semester by:

- Reducing student dropouts
- Improving students' learning and understanding
- find which content is relevant for a given user
- Improving training and learning materials

3.2 Data Mining Techniques used to Solve Adaptive E-Learning Challenges

We will list some of the adaptive e-learning challenges and data mining techniques used to solve these challenges:

1) *The coursework and exam-based assessment gap problem. They used Random Forest and Naive Bayes classifiers, [10].*
2) *How to predict student performance while using the system to learn They used supervised machine learning, unsupervised machine learning, SVM, and linear regression, [11].*
3) *How to help students in selecting their courses? They make use of the J48 and K-Means algorithms, [12].*
4) *How to group students according to their activity on the system. They use the fuzzy technique. Naive Bayes Classifier, Tree C4.5 Algorithm, [13], Linear Fuzzy Real Logistic Regression.*
5) *Predict the rate of graduation for the students. They use Decision Trees, J48, and Random Trees, [13].*
6) *predict the impact of the student's performance on the system and the measure results of their final assessment. They used Random Forest, Decision Tree, Naive Bayes, and Logistic Regression, [14].*
7) *How the institutions select better teaching and learning methods, like making a suitable timetable and teaching courses. They use K-means, Apriori Algorithm, [15], [16].*
8) *How to predict which students are likely to fail a course by tracking their assessment grades early in the system and increasing their learning time to reduce failure records. They use SVM (support vector machine classifier), [17].*
9) *Finally, how to build a system and find the outlier students that match the admission selection criteria. They use a data mining admission model*(DMAM) using Rule Mining, [18].

3.3 BrainHex Model Classifier

BrainHex, [19] ,is one of the most popular surveys used today with e-learning, adaptive learning, and gamification websites to detect the users' styles and then build a system adapted to their preferences and personality.

BrainHex is the result of many years of studying neurobiological research papers and trying their findings to the reality of game design and player satisfaction modeling, as well as several previous surveys into gaming such as the first demographic game design model DGD1 survey (which resulted in the DGD1 model) and the DGD2 survey (which directly affected the development of BrainHex).

Table 1. Description of brainhex model, [19].

BrainsHex's Model	***Description***
Achiever	Goal-oriented and motivated by completion. They like to collect and complete everything they can find. They prefer to carry out a series of tasks within their reach, distinct from Conquerors, who prefer to overcome difficult obstacles.
Conqueror	Enjoy struggling against strong opponents until they achieve victory. They channel their anger to achieve victory.
Daredevil	Motivated by excitement and risk-taking by playing on the edge. They enjoy rushing around at high speed while still being in control of the experience.
Mastermind	Solving puzzles, devising strategies, and making the most efficient decisions. They feel rewarded for making well-thought decisions.
Seeker	Exploring the game world and enjoying moments of wonder. This motivation comes from the parts of the brain that process sensory information and memory association
Socialiser	Interacting with other people, talking to them, helping them, or just hanging around. They are trusting and their behavior connects to their social center in the brain.

4 Gamification in E-Learning

Gamification methods and ideas are used in learning to motivate students in their learning process to complete the course, like finishing a game level with badges, leaderboard, and stars.

4.1 Gaming Categories in Learning Systems

The four most popular types of gaming used in e-learning, [20]:

1) Game-based learning acts like actual games added to the teaching methods in the classroom and the use of video games to gain high attention and motivation of the students during the learning process.
2) A Serious game is an adaptive gaming method used in schools to build a link between technology and pedagogy. It appears to the students like an ordinary game.
   List of serious games types, [21]:
- Teaching game: it is used in a full game environment to teach a concept of learning materials.
- Simulator game: it offers a virtual version of a stable practice and testing of an object from the real world.
- Meaningful game: it conveys the meaning with a meaningful message.
- Purposeful game: it needs to increasing users' activities and evaluate or measure users' ability to creates a direct real-world.

3) Gamification, [20], in education is a serious approach to accelerate the curve of the learning experience, teach complex subjects, and systems of thought"
4) Simulation: it's used to let students try the simulator system on the experiments and has many various input variables, observe the outputs, and record the results just like in a real laboratory. It allows students to try more practices safely and gain high benefits from this learning method.

4.2 Types of Gamers

Much research is done on how to detect the user's player types in the gamified learning system and categorize them based on his interaction with the system environment. The individuals' player, [22], [23], characteristics depend on context and environment. The important criteria that must be taken into consideration are the relationships between the users and their preferences.

The work, [21], presented the Hexad user type of model. The Hexad is a gamification user types model created to capture the users' motivations and different styles of interaction with gameful systems.

This model proposed the following six user types:

1) Philanthropists are motivated by intent. Without seeking a reward, they are altruistic and eager to share.
2) Socializers are inspired by togetherness. They want to communicate and build social relations with others.
3) Free Spirits: autonomy and liberty empower them to express themselves and behave without external interference. Inside a system, they like to produce and explore.
4) Achievers: competence motivates them. By completing tasks, they strive to advance within

a system or show themselves by solving hard challenges.

5) Players: external rewards or bonuses inspire them.
6) Disruptors: the creation of transformation influences them. They prefer to test the limits of the system and disturb the system to force negative or positive effects, either directly or throw others.

5 Related Work

In universities and schools, the student data size is increasing every year. So, we need to analyze this data and extract useful information using adaptive learning and educational data mining techniques.

In this section, we will list many research papers that used data mining in education to solve the e-learning challenges and how they solved these problems.

One of the challenges faced in the educational classroom is that every teacher needs to make the student's assessment as a paper on the university, but Orlando, etl , [24], solve this problem by building a new system for evaluating students in undergraduate courses to let students interact with him through this system.

The authors, [24], designed an evaluation model named ‘Leonardo’ to evaluate the student's work over the system and this system didn’t remove the teacher from evaluating the student and acquiring the knowledge over time.

The system lets the student take many quizzes and save the grades with some features The system controls the assessment like timed questions and how many questions are selected for the students from the chapters they have learned on the system. Based on the student’s questions and grades, he suggests a new material focus on the question chapter he gets low grades.

Figure 4 shows how this system works and interacts with the student. One of the defects of this system is that he didn’t save the student's behavior after logging out from the system. Every time a student logs into the system, he will be assigned the same material as a cold start and a new user to the system.

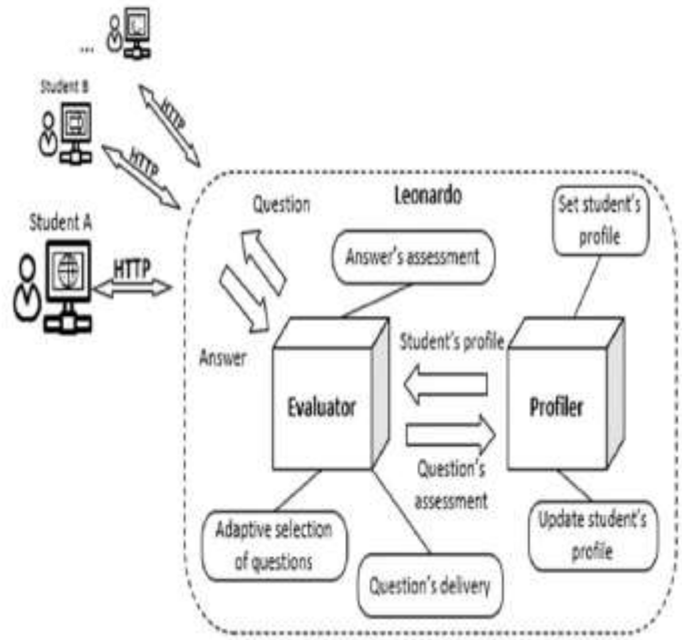

Fig. 4: Evaluation and profiling modules interact.

Lennart E. Nacke. Etl, [19], built a model called BrainHex and used surveys and questionnaires to classify users based on the results. This survey was conducted for more than 50,000 players. This system is like a game and classifies the user's type up to seven learner styles: Daredevil, Mastermind, Survivor, Seeker, Conqueror, Socialiser, and Achiever.

They collect some demographic information about the players and users to build relationships between players personality types and BrainHex model archetypes. A lot of researchers used this paper to build a gamification e-learning model for students to increase engagement with online education.

Evgenia Baranova, etl, [25], one of the important parts of the Russian Federation is to digitalize the economy, and education is an important part of this strategic goal.

The researcher used a digital education environment to analyze the data generated from the system to calculate the correlation between the online structure data, educational programs, students' behavior, and performance in the system.

They collect their data over 10 years from the university on various aspects of the educational process. calculations were made to find the conclusions about the nature of relationships between the selected features (the number of activities on the course, the participation of students in the course chat(s), the final assessment results for the course, the time student spent on the course) obtained as part of the student's work in the Moodle distance learning system (Moodle DLS) and the results of the midterm assessment.

Authors find that the activities may help in measuring various disciplines and preparing recommendations for updating educational resources to improve their quality. Just like when the student spends less time online and has a low grade on the midterm and his activities on the system are low his final grade will be low, and the system measure all these factors and find which students are likely to fail in this course to send a notification to the teacher to follow these students before the end of the semester.

Chrysalis, etl, [6], propose innovative adaptive learning based on two sources: the student and user personalization information and their learning behavior or style.

Firstly, to determine the first user behavior the system suggests a test to the user that asks about his learning style, based on these test results the system will store this result and adjust or adapt the learning material according to his style.

Secondly, they also used The Machine Learning Management (MLM) component/module to access the dataset that is formed from the Query Results Management component (QRM) and for feeding it to the actual machine learning algorithm.

This use case discusses how the system works. A user (from here on known as learner 1) logs into the system for the first time. Following that, learner 1 is given an introductory Test to determine his or her level of understanding. Based on this, the algorithm may suggest some further study links, tutors to contact, or even additional examinations. Let's pretend that learner 1 chooses Topic 1 and takes Test T1 after this initial phase. He gets a perfect score of 30. Based on the score obtained (and assuming a performance criterion of 40 or 50), it is clear that learner 1 requires additional support and assistance in Topic 1. The experiments were performed with 300 learners to show the impact of learning styles on learners' preferences in this system.

Élise Lavoué, etl , [26], built an automatically adapting gaming system for learning environments This system uses gamification ideas with the learning system to help increase users' motivation while using this system. They get help from experts to build this gamification system to build their website and the user's adaptation model for the French language's spelling and grammar learners The project, named Project Voltaire, was developed by the Woonoz company, which specializes in memorization software.

They announce their project and ask anyone to make a survey and fill in their data if they like to take and try these experiments via their websites. 266 participants were asked to try this website and follow these experiments to the end. In the second step, they divide the participants into three groups randomly: the first group will engage with the fully adaptive gamification system and the second group has fewer features of an adaptive system and the third group has no gamification or adaptation on their system or learning material.

After dividing the users into groups (the first and the second group), they will build the user's profile system initialized through the BrainHex survey that remains identical during the learning activity time. For three weeks, they first cluster users using this survey and develop five gaming features corresponding to different player types in the system. Then the adaptive system will display the learning material based on the experts' gamified learning material they suggest from the beginning.

They make analyses and study the experimental results. They use the user's time spent on the system and the learning environment. They find the results for the survey of enjoyment and gamification environments has the greatest number of engaged users than another non-gamified system. They should make a questionnaire or a survey during the learning process to know if the users enjoy this learning style or not, if they need to complete these experiments at the end of the three weeks, they find several learners didn't complete the survey and the learning materials. Also, they talk about how an incremental construction of the user profile could alleviate the issue of the preliminary BrainHex questionnaire.

Ramlah Mailok,etl, [27], in their need to develop digital children's games players aged 8–10 years by using the brainHex model survey in their study involving 214 Malaysian children. They need to answer a question if there's a relation between the brainhex survey results and differences based on age or gender. After their experiments, they found that achiever, daredevil, and conqueror emerged as the most dominant characteristics of all children at these ages, and all developers of digital games can help players, notably young players, or children, to develop sound thinking skills.

Jalal Nouri, etl, [28], The flipped classroom is used in this research topic as one of the learning methods because it's one of the pedagogical methods that finds the highest combinations of physical lectures and digital learning environments, like blended learning environments. The Flipped classroom is based on recording a video for all lectures and uploading all learning materials digitally on a website and finding the interaction between the students and these materials. The interaction between the students and the teacher is achieved by using discussion forums and digital quizzes.

Jalal Nouri, et al, [28], applied the system using 255 students. Students at Stockholm University who were given the course on research methodology in autumn 2017 needed an analysis step, to do more tasks as a group, and make a physical lecture to measure the understanding of this uploaded material with the teachers. This system also uses more prediction methods to find how many students may have passed or failed the course and detect the students' performance on this course using many techniques and machine learning methods like (i.e. Neural Networks, Naive Bayes, Random Forest, kNN, and Logistic regression). Additionally, the system takes into consideration the number of clicks on the material for every student and predicts based on his clicks on the system if he will pass or fail at the end of the course.

Author's experiments finds that the KNN prediction method has the highest accuracy for the results if passed or failed students at the end of the course, and if the students have less than 1355 clicks on the system, they fail in the course because they didn't study the material well enough and their results on the digital quizzes are less than 57 percent of the total marks. Finally, the flipped classroom was a good method for training students on the material before making a discussion and applying the training task with groups in the physical lectures, and it had a great impact on students in the learning methods.

Siti Nurul Mahfuzah Mohamad,etl, [29], This research idea builds a learning environment for students based on their intelligence. Gamification is used in this learning environment and makes the ending and studying of the learning material like a game. If you finish all tasks and assignments early, students will get more marks and grades. All the time, students must keep straggling and survive to gain more marks to get the rewards and not die and fail at the end of the course. This gamification learning method will develop students' critical thinking skills, increase their ability to work in a group, and allow students to give marks and grades for some assignments in the course, adding to the final marks.

Experiments in this learning method were applied to two groups of undergraduates from two TVET institutions in Malaysia; group 1 has 36 students and group 2 has 34 students studying the multimedia course. There are five phases involved in this study:

1) Determining Student Intelligence by taking a quiz and selecting which level to start the course.
2) Defining Learning Goal: design the learning material more interactive and make assessment creative and design activities with proper game elements.
3) Structuring Learner Experience: they must select the more appropriate game types that can be used with this subject and helpful to let students enjoy learning time all this semester.
4) Analyze Suitable Game Elements: the system interface and usability for all students selects 12 game elements to be added to the system list in Table 2.
5) Heutagogy Design Process: train students on how to use the technology and how to solve the assignments because this course is a multimedia system that teaches students how to make an online presentation, poster design, creative platform, problem-based learning, how to connect with Adobe Education Exchange, drag and drop activities, and how to solve crossword puzzles.

Using The gamified E-Learning site (OMIG), [29], is also embedded into LEARN, as well as linked to OpenCourseware (OCW) and Eg-MOOC. The new idea in OMIG, students can go to the next level in the learning process based on student intelligence and the results from the first MI (multiple intelligence test). Authors publish this link to be public to allow students to learn online http://onmitt.net/omig/index.html,https://www.flipsnack.com/995DFECF8D6/a-online-delivery.html.

At the end of this multimedia gamified course, they find that successful gamification needs to adapt to students' intelligence and provide suitable teaching materials to master their skills. Creative educators can make intelligent materials more attractive to students with a simple way to learn.

Table 2. Top Twelve Game Elements

No	Gamification Instruction	Interaction Dimension Gamification Elements
1	Learner-Content	Virtual Goods
		Wally's Games
		Memory Game
		Check Points
2	Learner-Instructor Trophies Badges Progress Bar	Rewards
3	Learner-Learner	Redeemable Points
		Skill Points
		Peer grading
		Peer Emoticon Feedback
		Team Leaderboard

Albert a.shawky,etl, [30], [31] ,built a technique to enhance the effectiveness of adaptive e-learning solutions and to create an effective online recommendation system, to correlate the student variables such as knowledge level and learning style.

This can be resolved by creating a new learner-centered model, [30], that incorporates learner style and knowledge level. Two efficient adaptive e-learning models are proposed. The first model for recommending materials is based on the prediction of the learner style using a questionnaire and adapted fuzzy c mean (FCM) , and the second one is for recommending materials based on a prediction of the learner style using a questionnaire and Learning Management Platform (LMP) score. In this model, questions and learning materials are mapped to each LMP. This model is a multi-level model that calculates the LMP values as well as stores the marks.

This system results show that the Adaptive fuzzy c mean system enhances the performance of the learner knowledge level by using the questionnaire and the adaptive FCM model has achieved the best performance at 88.7%. Moreover, the second contribution called an adaptive e-learning recommender model based on Knowledge Level and the Learning Style (AERM-KLLS) achieves the highest accuracy at 90.97.

Przybylski et al, [32], This researcher finds out how video games meet these psychological demands, by proposing a motivating model based on Self-Determination Theory (SDT).

Consider the following scenario: Obtaining feedback and demonstrating improvement will reward you. Then providing options for methods and possibilities will satisfy the sense of competence. Autonomy and competitiveness in the leaderboard and forum cooperation will meet the needs of the participants.

Reem S. Al-Towirgi, etl, [33], Students used a gamification system to learn the data structure course to evaluate students while using the physical teaching methods in the classroom and to evaluate the students' grades while using this gamification data structure course. They built a gamified course using the Moodle platform and used a more attractive user interface, themes, more fonts, and colors to make the system more enjoyable to the students. They used many levels in this system like Avatar, Options in selecting topics, Options in determining badges, Progress, Challenges, feedback, and Leaderboards. To satisfy the competence needed according to Self-Determination Theory (SDT), satisfying these three psychological needs will enhance the self-motivation of the students.

They conducted exterminates for 40 students of the data structure course. Firstly, they made an introduction to the course and illustrated how to use the system to get more points.

Firstly, students log in to a gamified course and take a pre-test to know the student's knowledge of the course and cover some course topics. Students will navigate the course and study the material via a gamification system. At the end of the course, students must take an online test to measure the effectiveness of the gamification on their learning outcome. Also, students were asked to fill out an online questionnaire about their feedback regarding their experience. A questionnaire will be used to measure student engagement. The final students' results and satisfaction with the overall gamification learning course have got high results compared to the teaching in the classroom.

6 Adaptive Learning with Facial Recognition

Uğur Ayvaz, etl, [34], E-learning has the advantage of providing more flexibility while we can discuss material online at any time with our students and solve the problem of student capacity. One of the main problems in e-learning is that we didn't use it face-to-face and didn't see the student reactions while we discussed the material and topics. They build a system used to take an image of the students' emotions while they use Skype online meetings. The teacher discusses how the material system will save these screenshots based on the students' emotions. They turn this image to give feedback to the teacher instantaneously. If students understand this material or not, whether they are happy, angry, or neutral, many different emotion types are used in their systems.

Uğur Ayvaz, etl, [34], build a system named a FERS to send a report about the students' emotions to the teacher this system used SVM (support vector machine) to make a classification based on students matching emotions and this system has more accurate prediction has 98% percentage to the real emotion saved before starting these experiments.

Duong Thang Long, [35], in this research paper, the authors need to solve the problem of how to identify the students in a learning management system. He attends the course and logs into the material online as a part of e-learning systems. The authors propose a new model based on convolutional neural networks (CNN) for human face recognition problems that has 5 convolutional neural layers (CONV) and 2 fully connected neuron layers (FC). This model can detect the student's images of different complexity and different light, like dark images, and it can crop the noise around the student's face to make more accurate results to identify the user. They train this model on different datasets like the AT&T dataset (also called ORL), which was created by the AT&T Laboratory at Cambridge University, in 2002. It includes 400 images of 40 people, with 10 different attitudes for each person.

The Yale dataset was created by the Computer Control and Visual Center at Yale University. It consists of 165 images taken from the front and on the multi-level of 15 different people.

The LFW dataset has a diverse number of images, ranging from 5 to 530. We just use people who have 20 or more face images. It is the so-called LFW20. So, LFW20 has 3,023 images of 62 people.

Their dataset, [35], was collected in an online class with 24 students. It has 1,005 face images, from the lowest number of 5 images to the largest number of 222.

This model is integrated with an LMS (learning management system). After the student logs in to the system with his user id and password, the system takes an image of the student using the CNN model and detects whether this account belongs to him or not by following these steps:

1) Open the client's camera to capture images of students. This activity is integrated with LMS on the client side for every student.

2) Preprocess captured images to get face images from the client's camera.

3) Recognize face images, [36], to get the ID of students or 'unknown' send notifications to LMS for announcing and monitoring the whole learning time of students.

Mohammed Megahed, etl, [37], The importance of adaptive learning environments to track the student's response while studying the material if they can go to the next level or need more practice at this level again. more systems of adaptive learning methods failed to capture the emotions of the students learning while studying the course. They build a new system to take screenshots of the students while studying the materials and taking quizzes by using an integrated system with CNN (conventional neural network) and fuzzy C-Means to cluster the students with the best knowledge level and their ability to study the next chapter.

In the proposed system Mohammed Megahed, etl, [37] , takes the responsibility for the exam and timed test questions and gives more different emotions to match his emotions and his grades in the system. Also, taking a screenshot of the students' learning time on the system can give the educator or instructor a brief about the student's grades expected at the end of the course. The system's main components are facial expression recognition, test, and exam manager, learning modeler, and fuzzy inference system. The importance of a fuzzy inference system is that it receives this data from the learner model to cluster students to the next learning levels or give more time to study the same topic again with more materials. The experimental results based on the corpora of 12 learners contain 72 learning activities and 1735 data points of distinct emotional states.

7 New Proposed Model

- (ILOs ADAPTIVE LEARNING WITH THE EMOTION-BASED SYSTEM)

We need to build an adaptive learning system to solve new problems and challenges today with the higher education about how to discuss the material with the students according to intended learning outcomes (ILOs), build a material to find and determine the knowledge level of students, and how the teacher will demonstrate this course to let students understand materials and which practical skills they will learn from the course.

This new proposed model will be adapted to the students' learning styles by making course materials fully engaged with pdfs, videos, and PowerPoints lecture materials. They will need to find their path by solving assignments and quizzes and how to get more points by solving assignments early and on the requested time. There are many models used to determine the student's learning style based on his activity on the system, like:

1. Kolb Learning Style Model
2. VARK Learning Style Model
3. Gregorc Learning Model
4. Hermann Brain Dominance
5. MAT Learning Model
6. Felder-Silverman Learning Style Model
7. Honey Mumford Model

We will use VARK. It will be suitable for our learning materials VARK (It stands for visual, auditory, reading/writing, and kinesthetic learning styles). This model states that every learner experiences learning through any one of these processes.

Our system will classify students based on their learner styles and suggest suitable learning materials like videos or reading textbooks or taking more practice with sheets.

Our material divides according to the ILO's the student will learn from every lesson he will study.

The main target of the system is how to make an exam that satisfies the ILOs of the course. Our system will choose several questions at the final assessment based on the question bank we build based on the learning outcomes from every lesson they study and which knowledge we need to measure through different assessment methods. Auditory learners frequently converse with themselves. Reading and writing assignments may be a challenge for them. They typically do better talk to a colleague or listening to what was said on a tape recorder.

To adapt this learning technique to teaching adaptive learning material, we follow these steps:

- We'll start with new material with a quick overview of what's the outcome.
- Finish with a summary of what you've learned thus far. "Tell them what they're going to learn, teach them, then tell them what they've learned," goes the ancient adage.
- Use the Socratic technique of lecturing by interrogating students to obtain as much information as possible from them, then filling in the gaps with your knowledge.
- Incorporate auditory activities like brainstorming, buzz groups, and so forth.
- Create an internal dialogue between you and your students' using chats and forums.

Visual learners have two sub-channels—linguistic and spatial. Learners who are visual-linguistic prefer to learn through written language, such as reading and writing assignments. Even if they do not read it more than once, they recall what has been written down. Even if they do not read it more than once, they recall what has been written down. They prefer to take notes and will pay more attention to lectures if they observe them. Visual-spatial learners typically struggle with written language and perform better with charts, demonstrations, movies, and other visual materials. They can quickly imagine faces and places using their imagination, and they rarely become disoriented by new learning methods. To incorporate this learning technique into the adaptive system, we add this feature:

- Include graphs, charts, pictures, or other visual aids in your presentation.
- Include reading and note-taking by writing comments like outlines, idea maps, agendas, and handouts.
- Leave blank spaces in handouts for taking notes and making comments.
- Ask them questions to keep them aware and allow space for discussion in the chat groups on the system.
- Use flip charts to depict what will happen next and what has already happened.
- Highlight crucial points to indicate when it's time to take notes.

Kinesthetic learners do best while touching and moving. You're at your finest. There are two sub-channels: kinesthetic (movement) and tactile (touch).

If there is little or no external stimulus or movement, they will lose concentration. They may wish to take notes while listening to lectures to keep their minds active. They prefer to scan the content first before focusing on the specifics when reading (getting the big picture first). Color highlighters are commonly used, and they take notes by drawing images, and diagrams. To incorporate this learning technique into the adaptive learning system, we follow these steps:

- Engage learners in activities that get them up and moving.
- Play music during activities when it is acceptable.
- Highlight essential points on flip charts or whiteboards with colored markers.
- Allow for frequent breaks for online sessions (brain breaks).
- Make sure you have highlighters, colored words, and sentences on your presentations and graphics on videos recorded.
- Lead students through visualization of difficult problems.

Our new system records the emotions, [38], [39], of the students while taking a quiz to make a report to the instructor on which part these students need more practice and to find the accuracy of the system between the system suggestion and the results of every question passed on this quiz.

Finally, our new system will solve more adaptive learning methods challenges and will let students engage with the system easily.

8 Experimental Results

Today, all schools and universities build an online learning system to help students learn and study all course materials remotely. It also helps teachers mark the students' assignments, quizzes, and exams online. To test our proposed model, we need to build the course materials to match with the course ILOs, and the materials must have videos, pdf files, and ppt to detect the learner style model. So, we test our proposed system on real course students at a university.

The system was online for students for three months from the start of the term to the end of it. This system is built using the NEO website.

The system has 310 learners studying the online course, Operations Research. The first week: starts by sending the students a link to our website and teaches them how to join this course via invitation through emails; collects data about the learner to initialize and create the learner profile. It also creates the domain model to help us discover the learner styles of students after tracking their activity on this website.

Table 3. Teaching and Learning Methods

Lecture	Brainstorming	Discussions	Tutorials	Problem solving	Laboratory & Experiments	Research and Reports	Role playing	Workshops	Projects	Modeling and Simulation

To build our new proposed models, we use the course ILOS first, based on the course specification and road map for the knowledge needed to be learned by students during this semester. The Teaching and Learning Methods as in table 3 and the Assessment Methods as in table 4 suitable for every ILOs (Knowledge & Understanding, Intellectual skills, Professional skills and General Tran. Skills) from the course.

Table 4. Assessment Methods

Written Exam	Practical / Exercise Exam	Quizzes	Term Papers	Assignments

After students register on the website and add their demographic data, we track the student's activity on our website to detect the student's learning style based on the VARK Model.

To Cluster students by K- means centroid based on their activity we used word net firstly to make nouns and sentences that define all these nouns and keywords match to all learner styles and keywords. Building a semantic map to match between these keywords to cluster students into 4 groups Visual, Aural, Read and write and kinesthetic figure 5 has all activity for students to match with any learner style like visual students like assignments, lesson, workshops, forums and wiki.

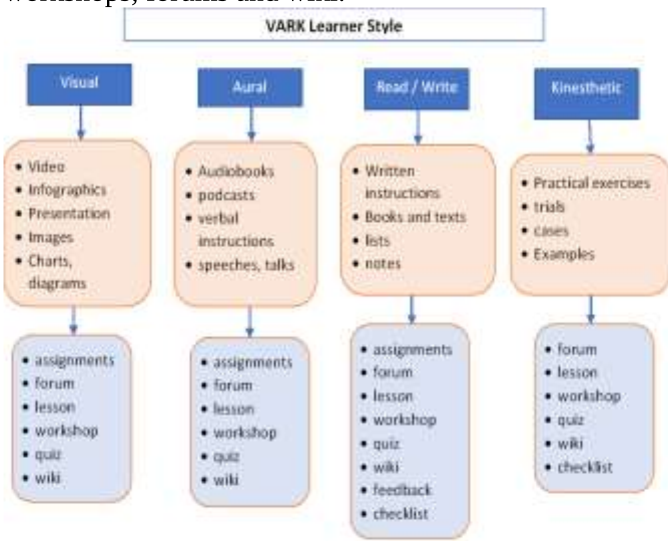

Fig. 5: VARK Learning style

We will list some of our system screenshots showing the model website contains materials and quizzes and assignments. Figure 6 shows the home page of the course. It contains 10 lectures, all different materials, has videos and pdf files assignment to let students answer these questions and try to solve problems.

Figure 7 shows The content for lecture 2 with video and pdf file for this lecture, Figure 8 shows the assignment content, start time , end time , grade , number of students submitting this assignment within time and number of students delayed in submitting this task. Figure 9 shows the content for the quiz questions created based on the ILos of the course.

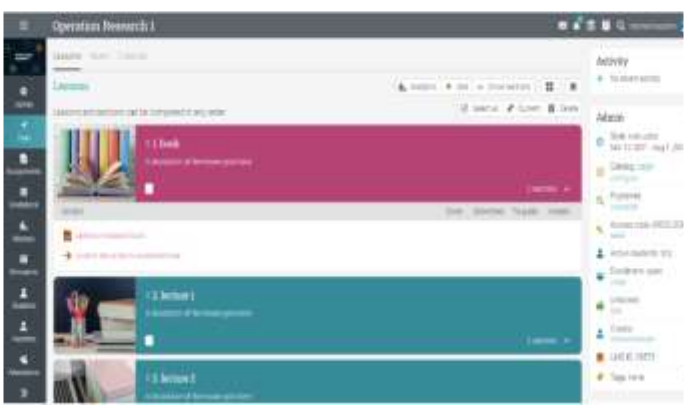

Fig. 6: Home page

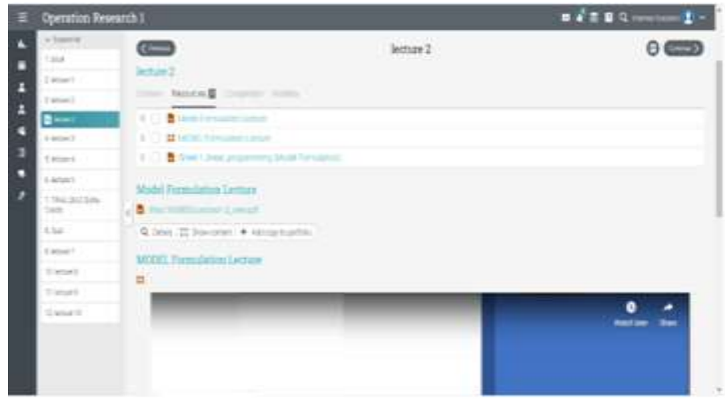

Fig. 7: Lecture 2 content

Fig. 8: The assignment content

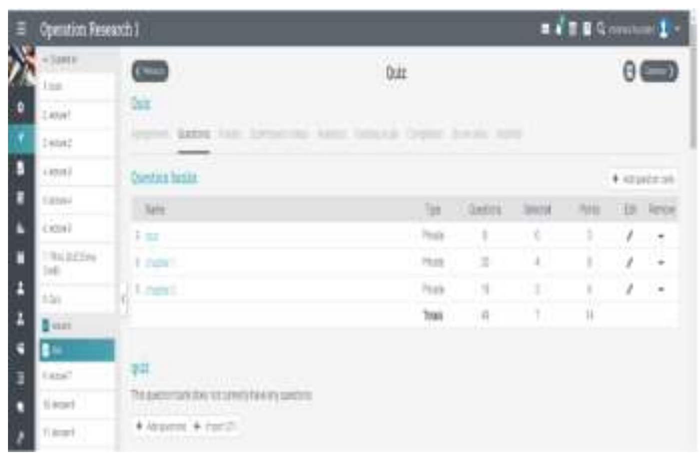

Fig. 9: The content of the quiz question.

Our model divides our students based on their activity. We found that the majority of students were visual learners (45%) and the rest of the sample students were kinesthetic and auditory, that is 30% and 25% respectively. Figure 10 represents the distribution of sample students' learning styles.

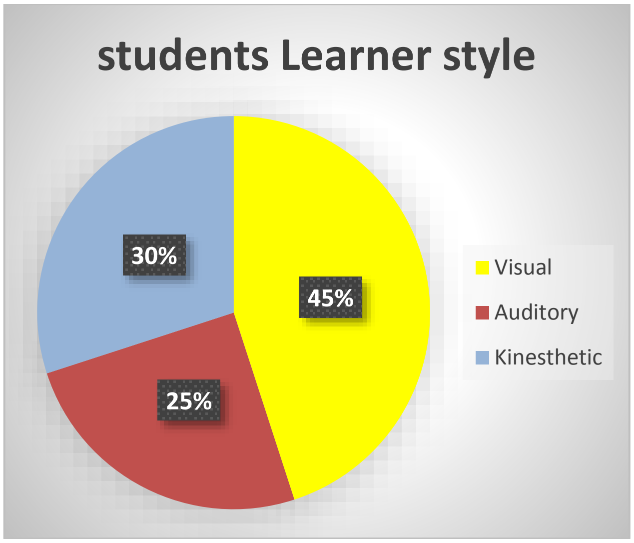

Fig. 10: learner style distributions

Finally, after the semester ends, we compare the students' grades while studying in our system to the previous year. Students study all lectures for this course physically on campus. We found that the grade scores for students increased this year and there was high satisfaction from the students' survey questionnaire.

Figure 11 shows the grades for every learner style. In this model we found that visual students have the highest grades followed by kinesthetic and the lowest grades auditory.

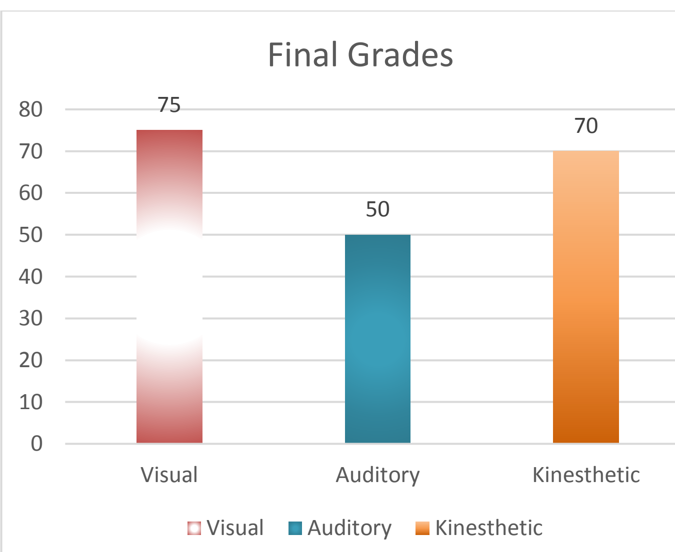

Fig. 11: Learner style and final grades

9 conclusion

Adaptive learning systems have the most important topics today. All researchers do a lot of systems to increase student engagement by using gamification to make lessons like a game with levels that must pass the first level and collect more badges or see the leaderboard list then can go to the next level. Other systems are used to classify students based on their activity on the site to detect their learner style and suggest the material. According to this report, many data mining techniques are used like clustering k-means, and classification like fuzzy c-means to predict results more accurately. Another system needs to detect the users' emotions while studying and while taking quizzes to predict their grade and which topic they need to study again.

Our new proposed system of ILOs adaptive learning with an emotion-based system will detect the student's learning style according to the student's activity on the site and then cluster students based on this style. The new idea is how to match this material with the ILOs of the course (Intended learning outcomes) as one of the most requested in learning today. The final step of the system is making the quiz match more questions based on the ILOs of the course engaged with monitoring the emotions while the students take the quiz to predict their grades and topics, he needs to study again according to the lowest grades.

According to this study, we found that visual learners like essays and demonstrating a process assessment; auditory learners like writing comments on lectures and like oral exams; and kinesthetic learners like MCQ questions and complete questions. So, we need to update our material to match all the learner-style assessments to let all students get high grades with the learning outcomes and preferred assessment methods.

future work, what about adding facial emotion tracking while studying this course material in our system and measuring the accuracy of prediction from this system and measuring the student's performance and the difference between studying the course in the classroom or using this adaptive learning system.

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