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Adaptive MOOCs: A Framework for Adaptive Course based on Intended Learning Outcomes

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This thesis was defended successfully on 24 / 01 / 2018 and approved by :

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Declaration

This is to declare that the thesis entitled "Adaptive MOOCs: A Framework for Adaptive Course based on Intended Learning Outcomes " under the supervision of Prof. Ahmad Ewais is my own work and does not contain any unacknowledged work or material previously published or written by another person, except where due reference is made in the text of the document.

Date : 24 / 01 / 2018

Name : Duaa Abu Samra Signature

Dedicated to

My Parents

My Brothers and Sisters

And

My Homeland ***PALESTINE***

ACKNOWLEDGMENTS

In the Name of Allah, the Most Beneficent, the Most Merciful.

Praise belongs to Allah, the Lord of all the worlds (2) The All Merciful, the Very-Merciful. (3) The Master of the Day of Requital. (4) You alone do we worship, and from You alone do we seek help. (5) Take us on the straight path (6) The path of those on whom You have bestowed Your Grace, Not of those who have incurred Your wrath, nor of those who have gone astray. (7)

Al-Fatiha

In the name of Allah, the most Merciful, the most Gracious. All praise is due to Allah; we praise Him, seek His help, and ask for forgiveness. Peace be upon the Prophet Mohammad, his family, his companions, and all those who followed him until the Day of Judgment.

Then, I would like to offer my deepest respect to my family, in particular, my father and my mother, the ones to whom I owe all the success in my life.

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LIST OF ABBREVIATIONS

MOOCs : Massive Open Online Courses

ILOs : Intended Learning Outcomes

OER : Open Educational Resources

ITES : Intelligent Tutoring Expert System

NN : Neural Networks

LO : Learning Object

LM : Learning Material

RR : Recommended Resources

P : Precision

R : Recall

MAP : Maximum A Posterior

SUS : System Usability Scale

DQL : Demographic Questionnaire for Learners

SIQ : Acceptance: Subjective Impression Questionnaire

WPQ : Workload Perception Questionnaire

ABSTRACT

Due to the increasing development in the educational domain, recent trends are pushing towards open learning environments (i.e., Massive Open Online Courses MOOCs) which offer many courses in different domains by a number of the top universities around the world. Accordingly, learners with different backgrounds and experiences around the world are able to browse and follow different online courses. Although the proposed systems to support adaptive MOOCs have many advantages over traditional online learning systems, they still suffer from several obstacles and drawbacks. On the other hand, the richness of courses in MOOCs could be also a weakness point. For instance, giving the opportunity to different learners to be able to explore a huge number of courses can cause many problems that will not enable learners to get the desired benefits and goals. This is because the courses level is not suitable for the learners or the courses contents which do not match intended learning outcomes (ILOs). Consequently , this is considered as a motivation in academic discussions on e-learning domain to support learners with adaptive online MOOCs based on ILO. This thesis proposes a novel adaptive MOOCs framework to support learners with suitable learning resources in MOOCs by adapting suitable learning resources and arranged them in a way that matches learner's profile. In particular, this work elaborates on the principles, requirements and models used for delivering adaptive MOOCs courses for classifying learning resources based on intended learning outcomes (ILOs). Additionally, this research proposes a conceptual framework to achieve the adaptation process automatically by employing Naïve Bayesian classifier techniques in MOOCs.

The proposed framework has been constructed and tested using learning materials collected from free coursera courses. Furthermore, the effectiveness of the used technique has been

validated using a precision-recall indicators and the results were compared with the manual results. After that, a pilot evaluation was conducted to measure the learners and educators satisfaction of the generated course based on the proposed framework. The results were promising as the precision-recall indicators provided a good results in the classification process. Additionally, the results of the questionnaire showed a good feedback and a positive impression from the point of view of educators and learners.

CHAPTER 1

INTRODUCTION

1.1 Introduction

According to New York Times, the year 2012 (Pappano, 2012), was considered as " the year of MOOC " where a number of the most famous universities of the world like Stanford, MIT, Harvard and Kyoto University started offering a series of courses in an open and free framework named as Massive Open Online Courses (MOOCs). The benefit of this framework lies in providing a set of learning platforms to serve a large number of learners who want to learn different online courses. Some of the proposed platforms are the edX, Coursera, Udacity, and FutureLearn are real models of these platforms. Based on the latest MOOCs report, the number of courses presented has increased from around100 MOOCs in 2012 to almost 6,850 MOOCs in 2016 from over 700 universities. Figure 1 shows the increase in the number of MOOC from 2012 :

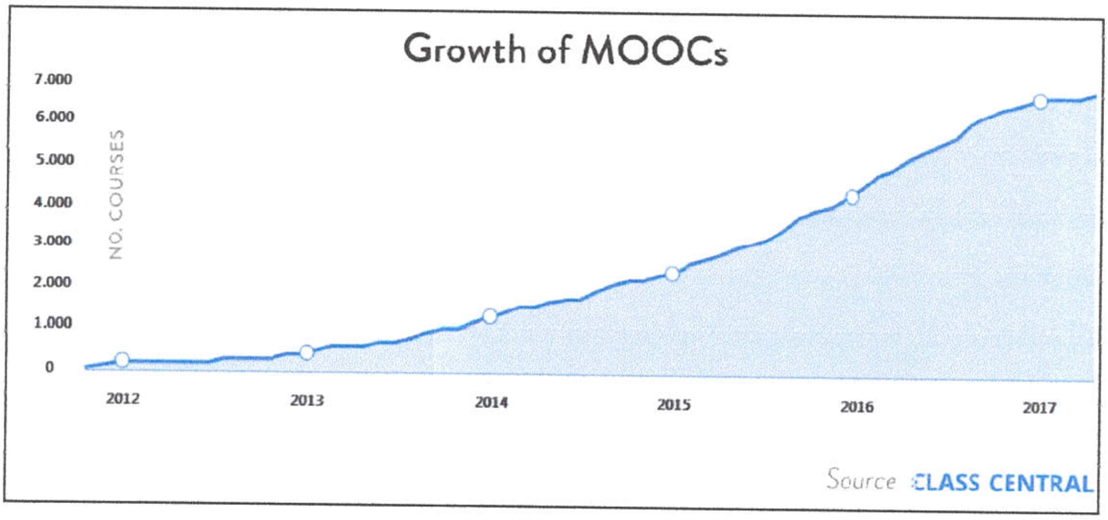

Figure 1: Growth of MOOCs (based on class-central report, 2016)

Currently, the development of MOOCs Platforms is in the center of attention associated to electronic learning domain. The great interest in MOOCs is due to the features that offers (Kahaei, 2015):

1. Scalability: MOOCs courses presented in open environments have been prepared to serve a huge number of learners.
2. Accessibility: learners can access to learning materials and resources in easy and flexible manner with giving the opportunities to learn from any geographical area.
3. Openness: MOOC supports free access to learning materials and resources over the web in any place and time for anyone that is concerned without certain qualifications.

Relatively, considering MOOCs as a new trend and they are in the early stages of popularity, there are different aspects required more investigation. For instance, motivating and encouraging learners to complete and finish their registered courses, publishing a wide range of online courses with different levels (beginner level, college level, graduate level, etc.), assessment criteria, accreditation, different quality of learning resources and learning materials, etc.

According to the literature reviewed in (Yousef, Chatti, Schroeder, Wosnitza, & Jakobs, 2014; Alshehri, 2015; Tseng, Tsao, Yu, Chan, & Lai, 2016), the vast majority of MOOCs learners are not active. Learners can be categorized into the following four groups: A group of learners who might register without logging in to the course. A second group follow learning path of the course without participating in solving quizzes and assignments. A third one is related to learners who read the learning materials and participate in different activities in the course such as solving quizzes and exams, contribute to teamwork assignments, etc. without completing the course. The last group who register into the course with submitting quizzes and exams and completing the whole course. However, there are several attempts to engage the previous categories of participants to be active by proposing novel techniques such as a game based learning (Romero, 2013 ; Sharples et al., 2016). Another approach is project-based learning which is another effective and enjoyable proposed technique to engage learners in the course (Irvine et al. 2013). Other approaches depend on generating active interaction, promoting thinking and providing feedback (Chin et al. 2010; Sharples et al. 2016). However, there is still a need to engage and encourage the student in the registered courses so that they reach to learning goals easily.

From this point, a novel adaptation framework for MOOCs has been proposed based on intended learning outcomes by exploiting the Naïve Bayesian Classifier technique (Yoo et al. 2016; Khatri 2012; Rish 2001; Rajeswari & Juliet 2017; Kaur 2014; Zhang et al. 2007; Witten et al. 2011; Murphy 2006; Jain & Mandowara 2016) to match the intended learning outcomes (ILOs) and the learning materials. By employing adaptation techniques from adaptive hypermedia domain, this research aims to deliver different types of learning materials such as (mp4, pdf, ppt.) with different levels of qualities (beginner level, advanced level, etc.) taking into account the learning styles for a learner like background, preference, experience, and ILOs. On the other hand, the Naïve Bayesian Classifier technique leads to retrieve recommended learning resources that are related to the learning materials from other courses which describe the same subject.

Based on the previous knowledge, no previous research work has been conducted to adapt and personalize the online courses using selected learning outcomes at the content level of a course, which distinguishes this research work.

The rest of this chapter is organized as follows: Section 1.2 presents the research motivations and the problem description. Section 1.3 describes the objectives that are considered in this thesis. The research methodology is presented in section 1.4. Section 1.5 presents the accepted applications in the field of Adaptive MOOCs. The organization of the thesis is presented in section 1.6.

1.2 Research Motivation and Problem Description

As mentioned earlier, during the last few years, MOOCs has expanded and adopted by people significantly. This led to a continuous growth in the number of offered courses and the quantity of learning resources over the Internet. Accordingly, MOOCs systems have many learners who are registering and following different MOOCs courses. Such learners have different fields of background, knowledge, expertise, specialization and intended learning outcomes (ILOs). Therefore, delivering learning materials and providing an additional learning resources (recommended resources) to the individual learner based on specific criteria can support the learning process. As a consequence, There are different systems and frameworks developed to consider the adaptation criteria based on learner style, preferences, knowledge, etc. that seek to ease the learning process by effectively processing the factual needs of learners.

Although the proposed solutions to support adaptive MOOCs have many advantages over traditional online learning systems (without adaptation), they still suffer from several obstacles and drawbacks. One of these drawbacks is to present all courses that are related to the objective of the learner without specifying the learning materials that should read to achieve this objective in an adaptive structured manner. Additionally, the learner can access other MOOCs courses outside his main area of knowledge, so it might or might not be appropriate for him (Gutiérrez-Rojas et al. 2014).

Another aspect is related to the wide range of learning materials with different types such as videos, slides, textbooks, etc. and different levels of details. Keeping in mind that there are a quite number of learners with a different background, knowledge level, culture, etc.(Onah & Sinclair 2016). For this purpose, some researchers have tried to employ learning materials in a lifelong learning process to suit different learners with different learning styles, interests and backgrounds(Gutiérrez-Rojas et al. 2014). Nevertheless, there are different proposals for applying adaptation to bridge the gap between the learner level and the learning materials provided to the learner.

Previously mentioned obstacles and drawbacks motivate this research to be conducted to decrease them by using both adaptation techniques and the Naïve Bayesian Classifier techniques to deliver learning materials of the courses based on intended learning outcomes ILOs. Therefore, the formulated hypothesize that "supporting learners with adaptive online courses based on intended learning outcomes selected by the learner will enhance the effectiveness of learning results". To validate the proposed hypothesis, this research work proposes a conceptual framework for considering the relationship between the different conceptual models such as learner models, domain model, pedagogical model, and adaptation model.

However, investigating the effectiveness of providing adaptive learning materials and resources based on the Intended Learning Outcomes (ILO) is not considered yet. Therefore, and unlike classical online learning systems (without adaptation), the proposed approach aims to pay more attention to learners through automatically generating learning path based on selected ILOs.

1.3 Thesis Objectives

Adaptive Online MOOCs Courses Systems aim to support learners in retrieving learning materials and resources depending on their skills, preferences, previous knowledge, needs and objectives from their profiles. This also means that such systems exclude learning materials and resources that do not match their requirements and needs. Newly, higher education institutions are moving to employ online Adaptive MOOCs systems in order to shift from a teacher-centered approach to a learner-centered approach. This shift serves learners in reducing the time, cost, effort and distance approximation so that anyone in any geographical area can register in the course and participate in the assessment (Gosling & Moon 2001). Despite the success of these systems in advancing and improving the learning process, they still suffer from a number of obstacles and limitations as mentioned in section 1.2 which can be attempted to overcome by discovering novel techniques or improving existing technologies.

The main objectives that we attempt to address and achieve during this research work are the following: the first objective is related to exploring the existing online adaptive learning systems. In addition, how adaptive techniques have been used to reduce the constraints on the learning process and serve the learners by meeting their needs based on their profiles. Moreover, another objective is concerned with applying the adaptation techniques in the proposed framework. Another objective is to investigate the possibility of employing intended learning outcomes and Naive Bayesian Classifier techniques in the domain of online education. In particular, this thesis addresses the following objectives:

- Exploring the current online adaptive learning systems and discussing how adaptive techniques are employed to help learners enroll in the courses and support them by providing the learning materials and resources that match learners profile such as level of knowledge, learning style, and learning outcomes.
- Mapping intended learning outcomes (ILOs) to learning materials. To do this, they have mapped them into two stages:
    1. Manual Mapping: This means inserting all intended learning outcomes for all courses and connecting them manually with the learning materials associated with them directly without having to use any techniques.
    2. Automatic Mapping: This is done through use the Naive Bayesian Classifier technique that classifies the learning concepts that should be considered in the course and ILOs into classes. Each class is mapped to learning materials included from a learning resources and materials repository that are related to learning concept. Consequently, the learning concept in each ILOs is linked to the related class.
- Proposing a framework to deliver adaptively learning materials and recommended resources based on corresponding learning concepts that are related to specific intended learning outcomes ILOs (determined by the learners themselves).

- Automatic generation of learning path based on selected ILOs. It specifies the path that the learner should pass to achieve the desired intended learning outcomes (ILOs).

1.4 Research Methodology

The research methodology that was followed to fulfill the mentioned objectives is divided into four major stages:

1.4.1 Stage One

The following steps present the main tasks that we carry out during this stage (more details are provided in Chapter 4 :

- The learner will select the general subject of the course and then a list of related ILOs will be displayed.
- Processing the learning materials and the intended learning outcomes (ILOs) to define the learning concepts that should be considered in the course and in the ILOs.
- The manual mapping between the ILOs learning concepts and learning materials concepts and assessment tools is built.
- As a result, the system will generate a course with learning materials that match selected ILOs.
- Also, taking into account the pedagogical relationship between learning concepts like *prerequisite-for, co-requisite for, defines, illustrates, etc.*. As such, it is possible for each learning concept to be mapped to one or more learning materials and recommended resources resource.

- After completing the learning materials that are related to any learning concept, a number of quizzes and exams will be displayed to determine if the learner understood the materials well or not.
- Based on the results of the quizzes and the exams, the learning path might be adapted accordingly.

1.4.2 Stage Two

At this stage, Automatic matching between learning materials and ILOs is generated through the following steps :

- Learning materials and ILOs are processed and refined in order to identify and create two lists of concepts. One of them belongs to learning materials and the other belongs to the intended learning outcomes ILOs.
- A Naïve Bayesian Classifier technique based on Maximum A Posterior (MAP) decision rule is developed to test if the learning material x_1 through x_n belongs to the learning concept class $C_K$or not.
- All classes of concepts are considered as a training dataset in Maximum A Posterior (MAP) rule to estimate decision variables depending on the frequency of the concept in each class in training dataset.
- Mapping between the concepts of ILOs and learning resources which are related to a specific concept will be generated.
- Mapping between the concepts of ILOs and recommended resources from other classes that are related to a specific concept will be generated. Resources with highest value of Naive Bayesian Classifier equation will be retrieved .

- A specific learning path will be provided for the learner by considering the pedagogical relationships between the learning concepts. For instance, the learner can't move to any concept if it is based on a previous learning concept that has not yet been mastered.

1.4.3 Stage Three

Unlike traditional online adaptive learning systems that carry out the presentation of learning materials with different formats as (mp4, pdf, ppt) in the same interface like coursera website without taking into account the learning style of the learner. Therefore, the goal of this stage is to integrate the learning style that the learner prefers in the learning process. Normally, the learner style is depending on visual or auditory style (Sancho et al. 2009). This is done by logging in the learner into his profile. After that, the learner identifies the format that he prefers to explore the learning materials and recommended resources by referring to it. Accordingly, all learning materials and recommended resources will be presented with the format selected in the learner profile explicitly.

1.4.4 Stage Four

To validate the effectiveness of the proposed online adaptive course framework based on intended learning outcomes (ILOs), it was evaluated in 3 stages: in the first stage, the Precision and Recall indicators were used in order to measure the quality of the produced results by the proposed framework. It is important to point out here that the dataset was collected manually. This dataset contains four courses named (Algorithms Design and Analysis Part 1, Algorithms Design and Analysis Part 2, mining massive dataset and Text Mining and Analytic Course) available through (Coursera) website and covering two different subjects (Algorithms Design and Analysis, data mining) with (1518) learning materials and resources in various formats such as (.pdf, .mp4, .ppt) and also it includes (48) different intended learning outcomes(ILOs). The second stage of the evaluation, a statistical analysis was conducted to a set of questionnaires filled out by a group of learners who have experimented the framework. The third stage of the evaluation, the effectiveness of the proposed framework was evaluated from the point of view of a group of educators. More details of these steps are presented in Chapter 5.

1.5 Publications

In this section, we list the recently accepted publications in the field of Adaptive MOOCs systems, those publications formulate the core of contributions in this thesis.

- Ewais, A. & Samra, D.A. (2017). Adaptive MOOCs: A framework for adaptive course based on intended learning outcomes. In: 2017 2nd International Conference on Knowledge Engineering and Applications (ICKEA). 2017, pp. 204–209.

- Ahmed Ewais and Duaa Abu Samra (2017). " Towards Adaptive MOOCs: Learner Oriented Approach based on Learning Outcomes". accepted by 2nd General Education Conference 2017 , Abu Dhabi .

- Duaa Abu Samra and Ahmed Ewais (Under Review). "Adaptive MOOCs based on Intended Learning Outcomes by Using Naive Bayesian Classifiers ". International Journal of Educational Development.

It is important to point out here that there are different parts of this thesis has been used from publications that have been mentioned above.

1.6 Outline of the Thesis

The thesis is organized as follow:

Chapter 2 presents brief description details on previous work and literature survey about online adaptive learning systems , adaptation techniques, and Naïve Bayesian Classifier techniques. Additionally, reviews related work dealing with providing adaptivity in MOOCs. Chapter 3 describes the adaptive conceptual framework and the proposed Adaptive MOOCs architecture based on Intended Learning Outcomes (ILOs). Chapter 4 explains the validation of the proposed framework. On the other hand, chapter 5 presents the evaluation of the results produced by the proposed system using precision and recall indicators. Additionally, conduct a descriptive analysis to a set of questionnaires filled out by a group of learners who have experimented the system. Also, discuss the system performance from the point of views of a set of educators. Chapter 6, concludes the thesis work and gives directions for the possible future extensions to the research work.

CHAPTER 2

LITERATURE REVIEW

The purpose of this chapter is to present a state-of-the-art related work that covers various topics related to the proposed research. Accordingly, this chapter begins with a background about the MOOCs courses, definition, types and purpose of creating learning platforms that provide courses for learners. Then, section 2.2 and 2.3 provides the adopted definitions of both adaptivity and learning outcomes. After that, section 2.4 presents a literature survey on current adaptation learning systems based on intended learning outcomes (ILOs),techniques used by online adaptive learning frameworks, and the obstacles of these learning systems. On the other hand, section 2.5 talks about machine learning algorithms and how can be applied in online adaptive MOOCs domain as an intelligent system in order to improve the efficiency of the learning process. Finally, summarize this chapter in section 2.6.

2.1 Background

Massive Open Online Courses (MOOCs) was introduced in 2008 by Dave Cormier and Bryan Alexander to present online courses belonging to the University of Manitoba (Smith & Eng 2013) and it is currently considered as an emerging trend in the technology-enhanced learning (Jona & Naidu 2014). MOOC comes from the following: 'M' refers to Massive which is related to the capacity of the course to expand to large numbers of learners. 'O' refers to Open which is related to providing Open Educational

Resources (OER) such as videos, audios, presentations files, notes, quizzes, tests, etc. regardless of participant's location, age, culture, background or any other registration requirements (Schuwer et al., 2013).'O' refers to Online which is related to providing synchronous and asynchronous accessibility of courses via internet connection (Stephen 2013).'C' refers to Courses which is mainly defined as an academic curriculum that is followed by learners (Voss 2013).

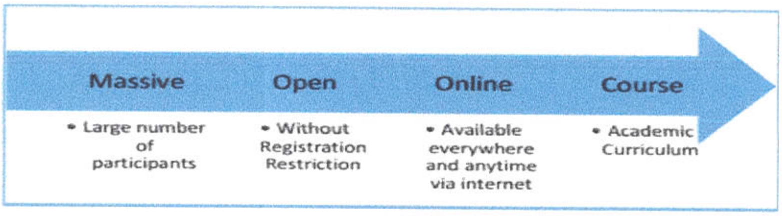

Figure 2: MOOCs abbreviation meaning (based on Voss, 2013)

Typically, MOOC is organized mainly into two types "cMOOCs" and "xMOOCs" (Smith & Eng 2013). The cMOOCs is mainly based on connectivism theory that supports the self-organized learning process, self and peer assessment to solve learning difficulties. In cMOOCs, the learners are actively participating in order to contribute in building their knowledge's through sharing learners' views with peers by using blogs of experiences and exploitation of existing resources such as articles, images, videos and social networks (Mccallum et al. 2013; Sammour et al. 2016). It also emphasizes that the ability to learn more is more important than the information known at present time (Smith & Eng 2013). On the other side, xMOOCs is mainly based on cognitivist, behaviorism, and social learning theories that support e-Tests provides predefined learning objectives by the teachers, and enable learners to communicate to each other inside the MOOCs platform itself. The xMOOCs is currently considered as a new technique of learning and teaching in graduate studies (Milligan et al. 2013; Baturay 2015; Rodriguez 2012). However, there are attempts to integrate the previous two types (Mccallum et al. 2013) or proposing new types with different characteristics as discussed in (Albó et al. 2015; Bali et al. 2016; Sein-Echaluce et al. 2016).

Although the shared goal of all MOOCs types is providing free and open learning to all people, each type of MOOCs has a different learning environment and distinct ways to acquire knowledge. Generally, the goal of MOOCs is to open education and a free access to university education for the greatest possible number of learners. Consequently, several learning platforms have been developed by various educational institutions to offer open courses either free or paid such as edX, Udacity, FutureLearn and coursera (Ardchir et al. 2017). Table 1 shows a good short description of some characteristics of the current learning platforms. on the other hand, we can also note from Table 1 that most of the learning platforms available today were established in a way that they mimic the traditional attributes in the presentation of the course contents, but in electronic manner. This explains the significant dropout in the completion rate of most courses offered by e-learning platforms (Samir R. Thakkar & Hiren D. Joshi, 2015; Ardchir et al., 2017; Vitiello et al., 2017). We think that applying the idea of adaptive learning in MOOCs platform in a way that encourages the learner to complete the learning process to the end can significantly contribute to overcoming the current problems in the low completion rate of courses in the learning platforms (Samir R. Thakkar & Hiren D. Joshi 2015).

Table 1: Summary of features supported by various MOOCs platforms (based on Ardchir et al., 2017)

	edx	Coursera	Udacity	Future Learn	Canvas Network
1. Learning Methods: *Video with Audio	✓	✓	✓	✓	✓
*Audio only	✗	✗	✗	✓	✗
* Articles	✓	✓	✗	✓	✓
* Projects	✗	✗	✓	✗	✗
* Discussions	✓	✓	✓	✓	✓
2. Assignments	✓	✓	✓	✓	✓
3. Quiz tests	✓	✓	✓	✓	✓
4. Transcriptions	✓	✗	✓	✓	✗
5. Video with interactive transcription	✓	✗	✗	✗	✗
6. Certificate	✓	✓	✓	✓	✓
7. Peer assessment	✗	✓	✗	✗	✗
8. Adaptive learning	✗	✗	✗	✗	✓
9. Course joining timings	Scheduled Anytime	Scheduled Anytime	Scheduled Anytime	Scheduled	Scheduled
10. Target users	Anyone	Anyone	Professionals	Anyone	Anyone

2.2 Difference between Adaptivity and Adaptability

Adaptivity is defined as actions that are done to adapt the information or functionality of the system based on specific requirements such as user needs and characteristics, context, device specifications, etc. For instance, Brusilovsky (Brusilovsky, 1996) defined adaptation in hypermedia domain as "all hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible aspects of the system to the user. In other words, the system should satisfy three criteria: it should be a hypertext or hypermedia system, it should have a user model, and it should be able to adapt the hypermedia using this model" (Brusilovsky, 1996). This differs from the definition of adaptability which is "the possibility for the learners to choose certain parameters of the learning experiences by themselves" (Akbulut & Cardak 2012).

Through these definitions, a clear definition of adaptive learning can be formulated that is "an effective way to improve the learning outcomes, that is, the selection of learning material and presentation should be adapted to each learner's learning context, learning levels and learning ability. Adaptive Learning System can provide effective support for adaptive learning" (Jia et al. 2010). Therefore, in the adaptive learning system, it can manage the available information and display the learning materials that meet each individual learner goals and needs in accordance to learner profile from learner model by using an appropriate adaptation methods and techniques. (Brusilovsky, 1996;Sanchez-Santillan et al., 2015; Gutiérrez et al., 2016). The proposed work is similarly aiming at providing adaptation learning based on learner profile such as knowledge, interests, background, etc. and also based on learning outcomes.

2.3 Learning Outcome

Learning Outcome (LO) is defined by the European Qualification Framework[1] as "statements of what a learner knows, understands and is able to do on completion of a learning process, which is defined in terms of knowledge, skills, and competence". Other definition by (Yildirim & Baur 2016), ILO is the learning outcome that is considered as a set of sentences that determine what the learner wants to achieve after success completing study the course content. So learning outcomes should be measurable and observable for knowledge, skills and attributes, as well as the actions must be carried out by the learner himself (Yildirim & Baur 2016). From the various definitions mentioned, learners outcomes are specified in terms of the level of knowledge, skillfulness, attributes, and

[1] http://ec.europa.eu/eqf/terms_en.htm

abilities that learners have obtained as a consequence of their participation in a particular learning process. Based on that, It can engage in increasing the level of involvement and knowledge in learners education. Moreover, it is clear that learning based on intended learning outcomes (ILOs) focuses on what the learner wants to understand and know after completing the learning process and learners accomplishments rather than focusing on the intentions of the instructor and learning materials as in traditional learning systems (expressed in the goals of the course or the unit)(Kennedy, 2007;Adam S., 2004). In this context, it is important to refer to a major education theory is Bloom taxonomy theory, which is often used in cognitive learning and was developed under the supervision of educational psychologist Dr. Benjamin Bloom in 1956 (Bloom, 1956). Bloom's Taxonomy separates the learning methods into three fields. Among of these fields is the cognitive field, which is often used in order to evaluate learner's performance through exams and assessments. Also, this field focuses on mental learning outcomes and divides the thinking into six levels beginning from the simplest recall to the most complex mental levels. These levels are illustrated as follows (Yugandhar, 2016; Halloun, 2017):

1. Knowledge :ability to memorize learning materials learned.
2. Comprehension: the ability to understand what the learning material contains of meanings and concepts.
3. Application: ability to employ the learning materials in new and implementable situations.
4. Analysis: the ability to return the learning materials to its basic elements so that its serial structure can be understood.

5. Synthesis: the skill of integrating the parts to form the overall structure.
6. Evaluation: ability to evaluate the learning materials for a specific goals.

From Bloom's point of view, education must focus on mastering learning material and the enhancement of higher levels of thinking for learners rather than taking facts and information as they are (Yugandhar 2016).

In the mid-1990s, a Bloom's Former student, Lorin Anderson, revisited and revised Bloom's taxonomy and introduced some modifications on the cognitive domain of learning taxonomy to reflect a more effective and accurate form of thinking. The most important of these modifications is to convert the six categories names from noun to verb form as well as reordering them (Anderson et al. 2001; Pohl 1999; Site et al. 1956). The following figure shows the original and revised leveled categories of Bloom's taxonomy (Halloun 2017; Anderson et al. 2001):

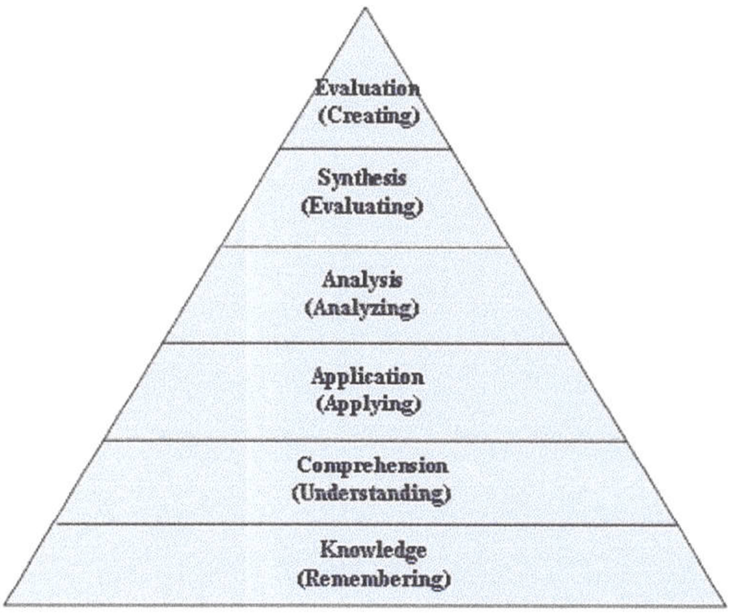

Figure 3: original and revised leveled categories of Bloom's taxonomy

Therefore, the proposed work is mainly depending on learner-oriented approach by considering the Intended learning outcomes (ILOs) defined and selected by the learners themselves. At the same time, the revised Bloom's taxonomy was adopted as a means for defining the learning objectives, assessments and learning outcomes.

2.4 Adaptive MOOCs based on ILOs

Currently, there are a limited number of attempts conducted to consider learning outcomes in the process of delivering adapted learning materials in the context of open educational resources (OER) (Hu, Li, Li, & Huang, 2015; Mossely, 2013). In general, authors in (Gosling & Moon 2001) pointed to a new direction in learning systems that involves shifting from teacher-centered to learner-centered based on the learner needs and intended learning outcomes. One of the shifting solutions is conducted by (Sonwalkar 2013) who proposed adaptation depending on five learning styles throughout diagnostic assessments about the participants' preferences and goals. Adaptation is considered depending on the used devices. Others (Gutiérrez-Rojas et al. 2014) proposed a prototype called "moocrank" to enable the learner exploring a number of recommended MOOCs based on the learning outcomes. However, the recommendation is done at courses level rather than learning materials so that the system will propose a list of possible MOOCs courses that match the selected learning outcome. Another interesting work (Rosen et al. 2017) provides adaptive assessments in MOOCs based on learner objectives. However, the proposed work is focusing on exams and questions rather than delivering learning materials of a course adaptively. Other related work is presented in (D. F. O. Onah & Sinclair 2015) which shows adaptation based on learners objectives to specify the learning path explicitly but it is not considering pedagogical relationships between the different learning concepts that formulate the learning path. More comprehensive reviewed related work can be found in (Alshammari et al. 2014; Leka et al. 2016; Sun et al. 2015; Sein-Echaluce et al. 2016; Lers et al. 2017; Ardchir et al. 2017).

From another point of view, some researchers as Teixeira et al (Teixeira et al. 2016) indicates that adaptive MOOCs can be considered as intelligent systems capable of adapting content and presentation to each learner according to their needs, objectives, and interests. This adaptation process is performed based on the learner decisions and adaptive engine which adapts the learning materials and resources according to learner model. In this context, it is necessary to mention here that the machine learning techniques are one of the most important techniques applied in intelligent systems. The following table summarizes all previous related works in terms of authors, year of publication, contributions, and the attributes that have been adopted in the adaptation to the proposed work.

Table 2 : Summary of related works

Authors	year	Contribution	Attributes that have been adopted in the adaptation criteria	Targeted platform
Gosling & Moon	2001	Pointed to a new direction in learning systems that involves shifting from teacher-centered to learner-centered	Learner needs and intended learning outcomes (ILOs)	E- traditional Learning
Sonwalkar	2013	Proposed adaptation depending on five learning styles throughout diagnostic assessments	Learner's preferences and goals	MOOCs
Gutiérrez-Rojas et al.	2014	Proposed a prototype called "moocrank" to enable the learner exploring a number of recommended MOOCs	Learning outcomes	MOOCs
Onah & Sinclair	2015	Proposed adaptation to specify the learning path explicitly but it is not considering pedagogical relationships between the different learning concepts	Learner objectives	MOOCs
Teixeira et al	2016	Considered the adaptive MOOCs system as intelligent systems capable of adapting content and presentation to each learner	Learners needs, objectives, and interests	MOOCs
Rosen et al.	2017	Provides adaptive assessments in MOOCs	Learner objectives	MOOCs

2.5 Machine Learning Techniques

More recently, a number of machine learning algorithms are applied in the online adaptive MOOCs domain to analyze vast amounts of complex data as well as extract information in order to acquire knowledge.

Typically, Machine Learning Algorithms can be organized mainly into two types "supervised learning" and "unsupervised learning" (Ardchir et al. 2017). Example of machine learning algorithms are decision trees (Topîrceanu & Grosseck 2017; Pandey 2013), support vector machine (Yahya 2011; Joachims 1998; Liu et al. 2013), random forests (Ghatasheh 2015; Breiman 2001), logistic regression (Anoopkumar & Zubair Rahman 2015), clustering and classification (M. Abdullahet al., 2016; Hämäläinen, Kumpulainen et al., 2013; Roy et al., 2017; Vitiello et al., 2017), neural networks (Hmedna et al. 2017), Fuzzy clustering and Fuzzy Logic (Bansal, 2013; Gowri, Kanmani, & Kumar, 2011; Verdu, Regueras, Jesus Verdu, de Castro, & Angeles Perez, 2008), Bayesian Network (Agarwal, Jain, & Dholay, 2015; Birari, 2014; Kotsiantis, Pierrakeas, & Pintelas, 2003; Almohammadi et al. 2017) . Such algorithms enable us to perform the prediction, classification, clustering, discovery new models, normalize and filter data for human judgment.

Example of adaptive learning systems that utilize machine learning techniques is Intelligent Tutoring Expert System (ITES) (Verdu et al. 2008). The proposed research employs a fuzzy method to evaluate the learners by building the exam sheets and generating the learning paths based on the progress in the learning process for each learner. In addition, Neural Networks algorithms (NN) have been used to support the personalization domain. It can specify and track the learning style for each learner, and provide the learning materials and resources that fit learners based on learning style during adaptive recommendation process (Hmedna et al. 2017). On the other hand, some authors suggested using the Naive Bayes Classifier technique to identify and adapt knowledge level of learner's in online test systems, and then determine the learner's actual ability and their competence based on performance analysis in online courses learning process (Agarwal et al. 2015). Furthermore, Bansal (Bansal 2013), offered the current efforts in the adaptive learning domain. He concluded that recommendation system must have four important characteristics: adaptation, low complexity, auto-updated and dynamic. This system was built by employing the fuzzy logic techniques (Alzaghoul & Tovar 2016). The following table summarizes the previous e-learning intelligent systems.

Table 3: Summery of e-learning intelligent systems

Authors	year	Contribution	Machine Learning Algorithm
Verdu et al.	2008	Evaluated the learners by building the exam sheets and generating the learning paths based on learning progress for each learner.	Fuzzy method
Hmedna et al.	2017	Supported the personalization domain and provided the learning materials that fit learners based on learning style	Neural Networks
Agarwal et al.	2015	Identified and adapted the knowledge level of learner's in online test systems.	Naive Bayes Classifier
Alzaghoul & Tovar	2016	Built a recommendation system with four important characteristics: adaptation, low complexity, auto-updated and dynamic	Fuzzy logic techniques

Accordingly, in the second phase of the proposed framework, a Supervised Machine Learning algorithm was applied, Naive Bayes Classifier, to link each concept in intended learning outcomes (ILO's) with related learning concept classes of courses. Accordingly, retrieve learning materials and recommended resources that are related to these concepts.

2.5.1 Naive Bayesian Classifier

Naïve Bayesian Classifiers technique is a simple probabilistic supervised learning model and in machine learning is a common classification technique depends on performing Baye's theorem with independence over-simplified assumptions between predictors (Agarwal et al. 2015). Bayes' theorem presents a method of computing the posterior probability $P(c|x)$ from likelihood $P(c)$, $P(x)$ and $P(x|c)$ (Riesenfeld 2011). Through the study of previous researches, naive Bayes classifiers are employed in many other different life domains such as e-commerce (Todi et al. 2012), e-News (Kaya et al. 2012; Ramdass & Seshasai 2009), medical diagnostics (Al-Aidaroos et al. 2012), adaptive e-learning system (Rajeswari & Juliet, 2017; Roy et al., 2017), testing system (Agarwal et al. 2015) and recommendation system (Khatri 2012) .

The reason behind the use of Naive Bayesian Classifier technique in this work is that it is easy to construct (Kori 2017), simple and relatively strong (McCallum & Nigam 1998; Kori 2017), accurate and fast (Krishnaveni & Sudha 2017), far from using complex repetitive variables which making it a beneficial model for small training datasets (Rish 2001; Korada 2012; Rajeswari & Juliet 2017). Moreover, the simplicity and high precision (Krishnaveni & Sudha 2017) that distinguish it and the ability to do the work in a way that surpasses the most advanced classification models as boosted trees or random forests models (Caruana & Niculescu-Mizil 2006; Korada 2012), makes it widely used in various real application problems (Rish 2001). It is generally used for document organization into one or more classes as email spam or not spam (Metsis et al. 2006), text classification (Rajeswari & Juliet 2017), sentiment detection (Caruana & Niculescu-Mizil, 2006;Zhu et al., 2017), management systems and medical diagnosis (Rish 2001).

Naive Bayesian Classifier operates under certain conditionally independent assumptions to work in a good manner. It makes two assumptions over features that are: 1) The previous importance of all features is equal. 2) All features are independent of each other, this means the impact of the value of the feature (x) on a specific class (c) is not related to the values of other features. Generally, these assumptions are not valid and often inaccurate, but in practical use, the algorithm yields good outcomes. Moreover, separating the conditional distributions of the class feature means the ability to handle each distribution individually as a one-dimensional distribution, this aids to minimize the problems that appear due to the dimensional curse (Niculescu-Mizil & Caruana 2005). Also, Bayesian Naïve Classifier algorithm has a set of specifications that distinguish it from other classification algorithms. For the classification it needs a small amount of training data to estimate the needed variables, it is quick and more efficient (Rajeswari & Juliet 2017).

Over the past years, some empirical comparisons between classification algorithms have been implemented by a number of researchers in the texts and documents classification domain. For example, in (Caruana & Niculescu-Mizil 2006), an empirical comparison has been performed between some supervised learning algorithms which are support vector machine, neural networks, logistic regression, Naive Bayesian, memory-based learning, random forests, decision trees, bagged trees, boosted trees, and boosted stumps.

The results indicated that the Naive Bayesian performance outperformed on the boosted trees or random forests models. On the other hand, the researchers in (Verdu et al. 2008) focused in their studies on applying the Naive Bayes as a text classifier for document classification and evaluated its performance against other classifiers. The results showed that the Naive Bayesian is the best in term of accuracy and computational efficiency against some common classifiers which are neural network, decision tree, and support vector machine. Additionally, attempts have been conducted by researchers in (Othman et al. 2017) to classify the web videos (MOOCs video) based on their metadata features such as (length of video, rate, comments,..., etc.). Therefore, Decision tree J48 and naive Bayesian algorithms has been used to perform the classification process. The results of both algorithms are compared and the Naive Bayesian was found more effective than Decision tree J48 algorithm to classify MOOCs videos based on their metadata.

2.6 Summery

The aim of this chapter was to present a literature review about the adaptive learning process in MOOCs platforms (traditional and current courses offered by online learning platforms). After that, MOOCs definition, MOOCs types and purpose of creating learning platforms were offered. Then, the adopted definitions of both adaptivity and learning outcomes were clarified. Moreover, this chapter talked about current adaptive learning systems based on intended learning outcomes (ILOs), techniques used by online adaptive learning frameworks, and the obstacles of these systems. Finally, the machine learning algorithms and how they applied in online adaptive MOOCs domain as an intelligent system were discussed in order to improve the efficiency of learning process in learning environment.

CHAPTER 3

PROPOSED FRAMEWORK

Before explaining the proposed solution, it is important to mention that the proposed approach for adaptivity is an author-driven approach. This means that the course author needs to define all possible adaptation techniques that can be applied to the course contents, presentation and navigation explicitly. This can be considered as a disadvantage. However, supporting authors with some usable and appropriate tools can solve such issue. It is also important to notice that this work does not consider the creation process of the learning resources and course contents as for this there are many available platforms and tools.

The structure of this chapter is as follow: Section 3.1 introduces the conceptual framework. Furthermore, important principles that are considered in proposing the conceptual framework are presented in section 3.1.1. After that, section 3.1.2 presents a number of functional requirements that have been formulated for providing adaptation inside MOOCs. Also, section 3.1.3 presents the different models that are considered in the proposed framework. After that, section 3.2 presents the general overview of the proposed adaptive MOOCs system as well as the two phases (manual and automatic classification) that have been performed. Finally, section 3.3 summarizes this chapter.

3.1 Adaptive Conceptual Framework

3.1.1 Adaptation Dimensions

As hypermedia systems have been used in MOOCs' deployment, several attempts apply adaptation techniques from hypermedia domain to MOOCs(D. Onah & Sinclair 2015; Lerís et al. 2017). The possible adaptation techniques in hypermedia are investigated thoroughly in the literature (Knutov et al. 2011; Conlan 2003; Brusilovsky 2004; Bunt et al. 2007). For instance, Brusilovsky(Brusilovsky 2001; Brusilovsky 1996) proposed a number of adaptation techniques which can be applied to content, presentation, and navigation.

The proposed adaptation techniques for content are defined as follow: *additional explanations* which is used to display or hide additional information, *prerequisite explanation* which is automatically inserting explanations of prerequisite learning concepts that the learner is not familiar, *comparative explanation* which is used to provide similarities and differences between related learning concepts, and the *explanation variant* which supports learner with different explanation about determined learning concept.

On the other hand, adaptive presentation and navigation support can be provided in the form of direct guidance, hiding, sorting, and annotation (Brusilovsky, 1996) depending also in specific attributes from the learner model. For instance, *direct guidance* is used to suggest a link to be followed from the current page. *Hiding* is used to automatically hide links to irrelevant learning objects. *Sorting* is used to arrange relevant learning object so that relevant resources are shown first while least relevant resources are shown last.

Finally, Annotation is used to annotate relevant links to learning objects with textual or verbal indication such as traffic light theme (green, orange and red) (Bra & Calvi 1998).

The considered adaptation techniques in this work is mainly depending on the Brusilovsky's adaptation techniques as they are considered one of the most popular in the domain of adaptive hypermedia in general. The proposed techniques clearly indicate what can be adapted and which techniques can be used based on specific attributes from the learner profile such as knowledge, preferences, background, etc. It is important to mention that this research work uses the ILOs as one of the attributes to be considered in the adaptation process.

Therefore, the adaptation techniques that have been considered in this research work are limited to adaptive presentation and navigation support techniques to validate the possibility of delivering adaptive MOOCs effectively. More adaptation techniques can be implemented in a future version of this work.

3.2.2 Framework Requirements

Based on the reviewed work in(Abdullah et al. 2015; Alshammari et al. 2014; Yarandi 2013; Baldiņš 2016), we derived some requirements to be considered in providing adaptive MOOCs course. The requirements are the following:

1. **Learner-oriented**: One of the current directions in education is to support learner-oriented education rather than instructor-oriented education. One of the possible requirements to support learner-oriented approach in the educational domain is to enable the learner to choose so-called intended learning outcomes for a specific

course. Moreover, considering the ILOs in the adaptation process can guarantee a certain level of learner-oriented aspects.

2. **Pedagogical-oriented**: As we are dealing with the educational domain, there is a need to consider different pedagogical aspects when specifying an adaptive course. This is achieved by considering pedagogical relations between the different learning concepts that will be covered in a specific course (Baldiņš 2016).
3. **Adaptive-specific:** Adaptation is an important aspect of enhancing online education. To achieve adaptation, there is a need to provide a repository of the adaptation techniques that can be applied to courses' content, representation, navigation and assessments (Brusilovsky, 1996;Brusilovsky, 2001; Brusilovsky, 2004).
4. **Web-based:** As we are considering the delivering MOOCs, a web-based delivering environment will allow easy access to different online learning materials. Also the system that will apply the proposed framework will be independent of the platforms or PCs that are used by the learners.

3.1.3 Conceptual Models Framework

Delivering Adaptive MOOCs can be done by maintaining information represented in different models similar to the classical adaptive systems (Alshammari et al. 2014; Leka et al. 2016). This work follows the same approach and the different models that are required are the domain model, learner model, pedagogical model, and adaptation model. The models are depicted in Figure.4.

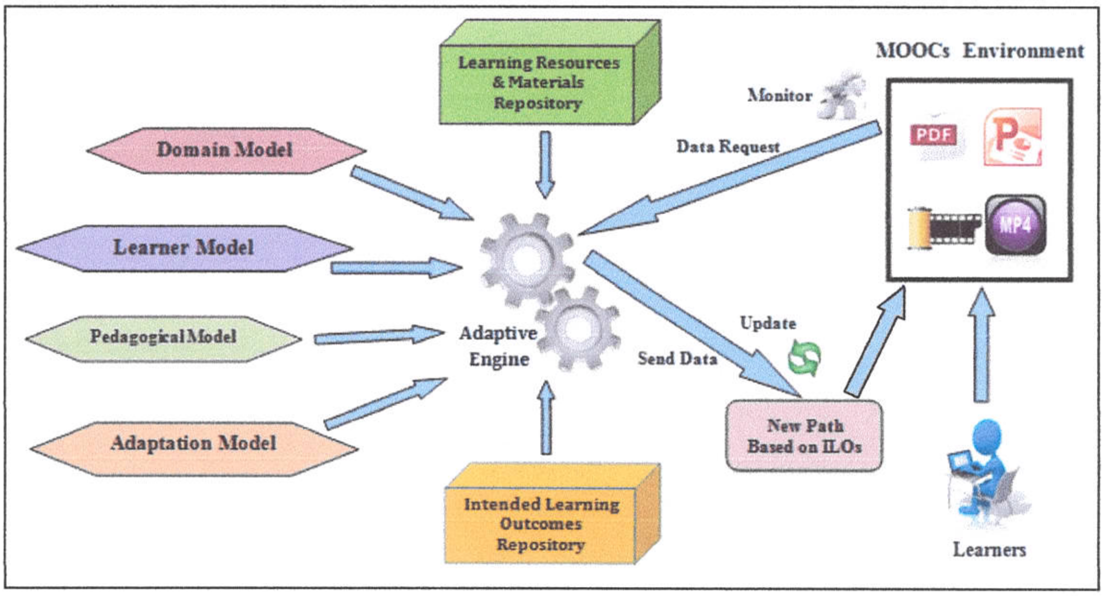

Figure 4: Adaptive MOOC Conceptual Model Framework

Starting with the domain model (Hendrix et al. 2008)which is used to describe the learning concepts that should be considered in the course, each learning concept has semantic relationships such as part-of and is-a with other learning concepts. Each Learning concept is mapped to learning materials or learning objects included from learning resources and materials repository. A Learning Object (LO) is defined as "a self-contained and independent unit of digital educational content, which is associated with one or more learning objectives and it has a primary aim in the ability of reuse in different educational contexts" (Nikolopoulos et al. 2012).

Furthermore, each learning concept is mapped to at least one ILO stored in the intended learning outcome repository. Therefore, an ILO can be mapped to one or more learning concepts. This mapping is used to show the percent of achieving or completion the learning outcome based on acquired knowledge of associated learning concepts. By completing the required knowledge about a number of learning concepts, then the learner will achieve the ILOs that are mapped to the learning concepts.

After that, learner's characteristics such as learning background, and learning progress are maintained inside the learner model. Learner model includes both static and dynamic data about the learner. Static data is related to demographic data about the learner such as name, gender, age, etc., which can be collected explicitly by asking the user to fill in a preliminary questionnaire. Other data can be dynamic such as learner preferences, skills, knowledge which will be updated during the learning process. A completed learning outcome is also one of the key elements of the learner model in the proposed approach as it is required for providing adaptivity. However, realizing learner model is not considered in this research work but attributes such as learner knowledge, background, interest, ILOs, etc. need to be supported to the adaptive engine to perform the adaptation process. For more details about learner modeling can be found in (Dolog & Nejdl, 2003; Long & Aleven, 2017; Moreno-Ger et al., 2010; Ardchir et al., 2017).

Another important model in the proposed framework is the pedagogical model which is used to define the pedagogical relationship types between the different learning concepts defined in the domain model. Accordingly, this will define the process of updating the learner model based on learner's progress. A typical example of a pedagogical relationship is that mastering a learning concept can update the knowledge of other learning concepts with the prerequisite relationship. Furthermore, The pedagogical relationship types define also the sequence on which the learning concepts should be mastered.

Adaptation model is responsible for realizing the adaptation process based on the concept of "IF-THEN" rules. 'IF' part contains the condition which will trigger the adaptation process and the 'THEN' part is responsible for defining the action that should be performed based on the satisfying conditional part of the rule. This concept of adaptation rules has been adopted by many researchers too (Rosen et al. 2017; Nguyen & Do 2008; Gutiérrez-Rojas et al. 2014).

Adaptation rules are defined at three levels. The first level is related to determining a course's learning concepts based on selected learning outcomes. The output of the first level is a course syllabus.

For instance, a rule can be defined as IF ILO-A is selected THEN Add all associated learning concepts to the list of learning concepts that should be acquired during the learning process.

The second level is related to defining an adaptive learning path depending on learning progress. The output of the second level is an adaptive sequence of learning concepts to be mastered by the learner.

An example of possible rules is IF learning_concept-X is prerequisite for learning_concept-B THEN learner will not be able to learn learning_concept-B until he acquires the required knowledge about learning_concept-X.

The third level is related to providing adaptation to courses' presentation and navigation. The output of this level is delivering learning resources, guidance towards related learning resources and arrange learning resources according to the appropriateness for the learner. This is realized by using the Bayesian algorithm and manually mapping the learning objects with.

For example, IF learner knowledge about learning_concept-X is more than threshold score THEN show advanced learning materials related to learning_concept-X. The threshold score is determined by an expert (educator).

Another responsibility relates to adaptation model which is to assist the learners in knowing the situation that has been accessed in the learn of a particular learning concept in the learning path. This research work includes four different situations which are: first, learning concepts that have been read and passed. Second, learning concepts based on previous learning concepts. Third, learning concepts that are currently reading and the last situation is the learning concepts that have not been read yet. Here, The adaptation is done by using different colors that distinguish each situation from the other. For instance a gray color is used to indicate on learning concepts that are based on previous learning concepts.

Finally, the adaptive engine is used to perform the adaptation process by compiling the predefined adaptation rules (in the adaptation model) as mentioned earlier. As a result, an adaptive MOOC course will be generated and updated based on assessments results (from the domain model, ILO repository and learning resources repository). The adaptive engine will send the required updates such as inserting new learning material, update learning path, quizzes, etc. using the update component. At the same time, a monitoring component is used in the MOOCs environment to record the learner activities and exercises results to be sent to the adaptive engine. As a result, the adaptive engine will update the learner model based on the predefined pedagogical relationships between learning concepts (from pedagogical model).

3.2 General Overview of the Proposed System

This section presents a general overview of the proposed adaptive MOOC system wherein the adaptation is applied using the manual mapping between ILOs and learning materials as a first prototype. After that, the adaptation is applied using the automatic techniques based on Naïve Bayesian Classifier technique to match the ILO and related learning concepts in order to effectively retrieve of learning materials and recommended resources based on specific criteria as a second prototype. It is important to mention that the development of the proposed adaptive MOOC system has been performed in two major phases which are described in the next subsections.

3.2.1 *Manual Mapping between ILOs and LMs*

Through this phase, the first prototype of the proposed adaptive MOOCs system was carried out based on matching between Intended Learning Outcomes (ILOs) and learning materials in manual manner. Therefore, a manual mapping between ILOs and learning materials is mainly done by defining the learning concepts that are related to both ILOs and learning materials. After these learning concepts that have been identified out of the ILOs are added to a specific list. Also the learning concepts that have been identified out of the learning materials are added to a separate list too. The two lists will be considered as an input for the adaptive engine to match each ILO with corresponding learning materials through the related learning concept. However, it is important to mention that the pedagogical aspect of the proposed system is realized by creating the pedagogical relationship between the different learning concepts. This will generate a learning path so that a specific sequence of displaying learning materials will be implemented.

On the other hand, in order to motivate the learners and enhance the learning process, the learning style that is determined by the learner in learner profile (mp4, pdf, ppt) is taken into account when retrieving the learning materials. Therefore, the learning materials that take the same learning style are displayed for the learner. Figure 5 depicts the first prototype of the proposed system.

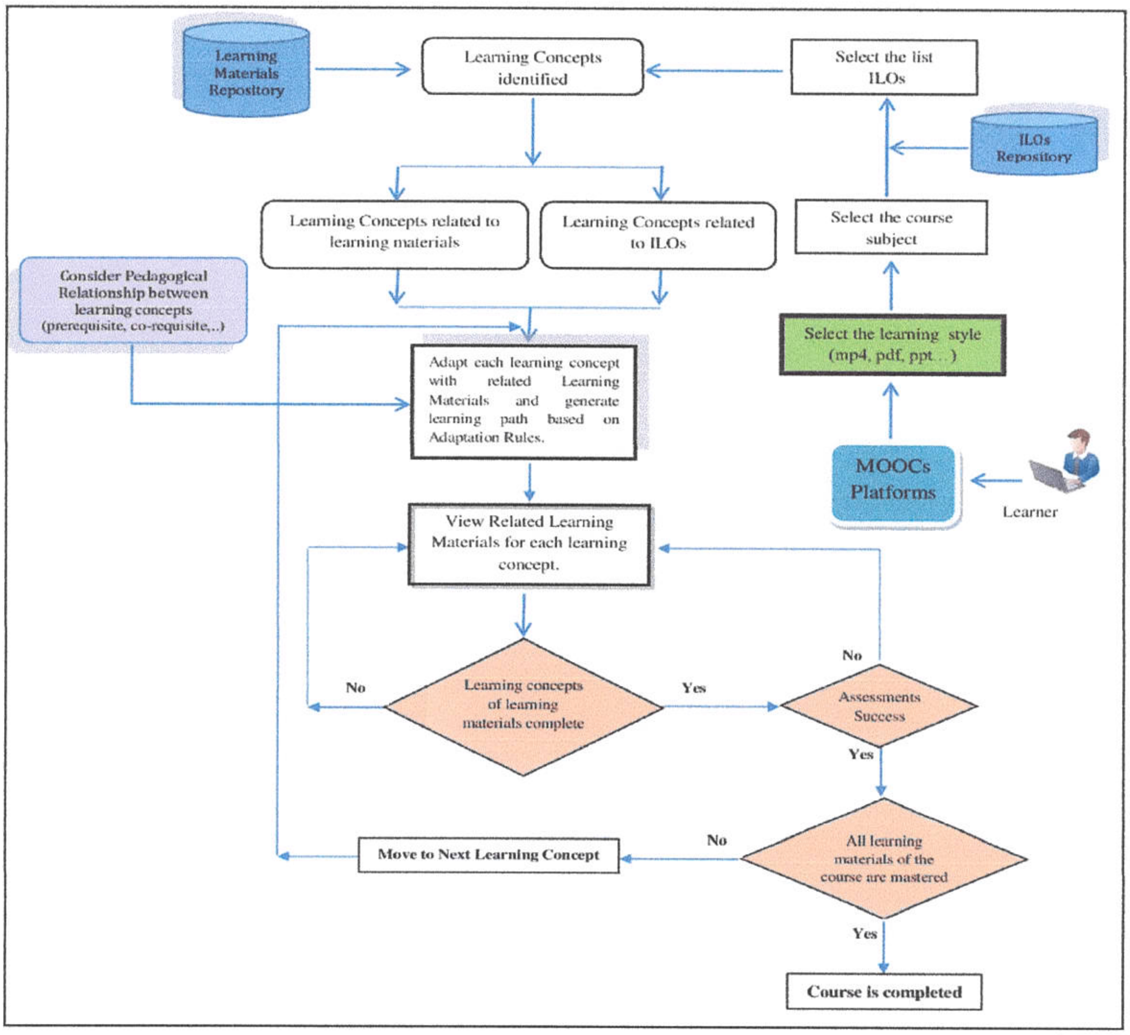

Figure 5: First prototype of the proposed system (phase 1)

As seen in Figure 5, the first phase of the proposed system includes several steps that are organized as follow :

The learner will be able to select the course subject that he would like to learn about. After that, a list of related ILOs, that are stored in the ILOs repository, will be displayed to be selected. The mapping between the course subject and ILOs is done by experts so that a list of ILOs are created and mapped to each course subject. This process is done manually.

Then, after choosing the required ILOs by the learner, an identification and extraction processes will be realized to match learning concepts of the selected ILOs with the similar learning concepts corresponding to the learning materials. For instance, a rule can be defined as IF ILO *"Explain the major algorithms for spanning trees including Prime's Minimum and Kruskal's Minimum spanning tree algorithm"* is selected THEN Add all associated learning concepts (**learning_concept_1:** *Prims minimum spanning tree algorithm and* **learning_concept_2:***Kruskals minimum spanning tree algorithm)*to the list of learning concepts that should be acquired during the learning of the generated course. As mentioned earlier, the generated course for a specific learner can be different than other learner depending on the selected ILOs.

After this step, the system takes these learning concept lists as inputs to provide adaptation to the presentation of the learning materials and navigation inside the course. Adaptation happens in two forms. The first, adaptation is realized based on moving from a learning material to next learning material after reading or viewing the displayed learning material based on acquired knowledge of the current learning material.

Currently, opening the learning materials and exploring it will enhance the learner knowledge about the associated learning concept. The second, adaptation is realized by generating a learning path of the learning concepts that will be studied during the course depending on the pedagogical relationships between the learning concepts.

An example of the first adaptation form is the following: IF learner knowledge about **learning_concept** : "*Prims minimum spanning tree algorithm*" is more than 75% THEN show advanced learning materials related to **learning_concept** :"*Prims minimum spanning tree algorithm*".

The second adaptation form is defining an adaptive learning path based on the pedagogical relationship between learning concepts. This leads to present an adaptive sequence of learning concepts to be mastered by the learner. An example of possible rules is IF **learning_concept** "*Prims minimum spanning tree algorithm*" is prerequisite for **learning_concept** "*Kruskals minimum spanning tree algorithm*" THEN learner will not be able to learn **learning_concept** "*Kruskals minimum spanning tree algorithm*" until he acquires the required knowledge about **learning_concept** "*Prims minimum spanning tree algorithm*".

As a result of employing previous adaptation rules, The learning materials that meet the needs of the learner will be provided. Also, the learning path that the learner will follow during the learning process will be presented.

To complete the learning process, the system offers assessments to evaluate the learner understanding of each learning concept after completing all learning materials that are associated with it. Consequently, if the learner does not exceed the assessments threshold score, then the system represents the learning materials that are related to the learning concept to be learned again. It is important to mention here that the mapping between the assessments and the learning concepts is also done manually.

3.2.2 *Automatic Classification of LMs based on the ILOs Using Naïve Bayesian Algorithm*

At this phase, the second prototype of the proposed adaptive MOOCs system was carried out based on matching between Intended Learning Outcomes (ILOs) and learning materials in an automatic manner using one of the most used machine learning algorithms is named the Naive Bayesian Classifier algorithm. Therefore, an automatic mapping between ILOs and learning materials is mainly done by defining the learning concepts that are related to both ILOs and learning materials. After that, learning concepts that have been identified out of the ILOs are added to a specific list is called ILOs learning concept list. Also, the learning concepts that have been identified out of the learning materials are added to a separate list too is named learning concepts of learning materials list. The two lists will be considered as an input for the Naïve Bayesian algorithm to do two main processes. The first process is matching each ILO with corresponding learning materials through the related learning concept. The second process is adapting each learning concept with corresponding learning materials.

The previous algorithm classifies all available learning materials into classes during the training phase. Then, it calculates all posterior probabilities for each learning concept in each class during the testing phase. As a result, the learning materials class with the highest posterior probability value for each learning concept are returned so that the learning materials in this class are presented for the learner to learn.

It is necessary to mention here that the Naive Bayesian classifier algorithm output only one value of posterior probability at a time. Therefore, an update to the algorithm was done to exclude the learning materials class with the highest probability value, and to be able to produce other three maximum values of posterior probability to be presented as a Recommended Resources (RR) for the learner. Figure6 depicts the second prototype of the proposed system.

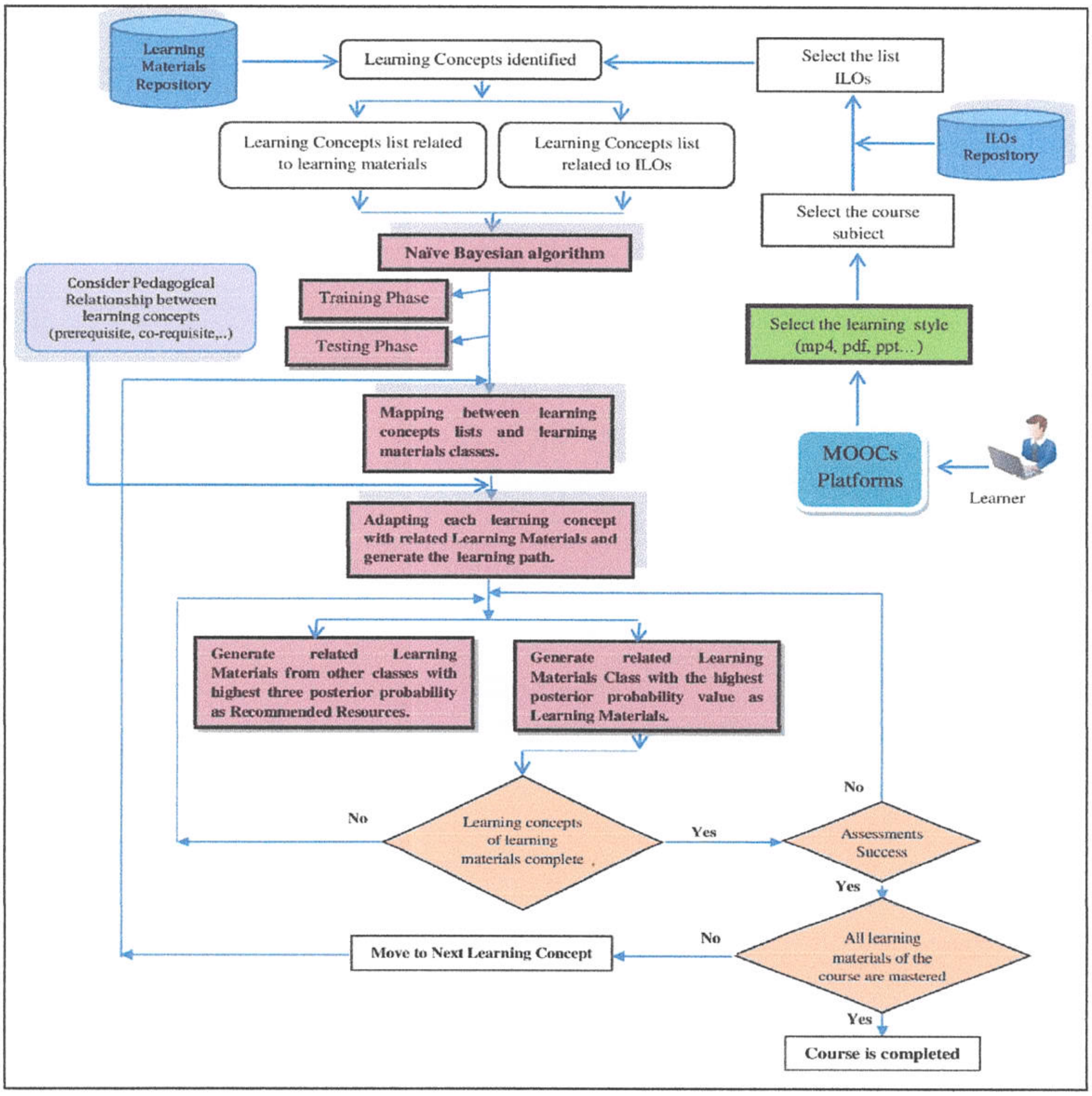

Figure 6: Second prototype of the proposed system (phase 2)

As seen in figure 6, after choosing a course subject and the required ILOs by the learner, an identification and extraction processes will be realized to match learning concepts of the selected ILOs with the similar learning concepts corresponding to the learning materials. So that, the system takes the learning concept lists of both ILOs and learning materials as inputs to Naïve Bayesian Algorithm in order to match between the learning concepts with related learning materials through two phases as follows:

Through the first phase, Naïve Bayesian Algorithm classifies the learning materials into classes. Each class contains a set of learning materials that are related to a specific learning concept. After that, all learning materials classes are entered into a training phase as a training dataset to map each learning concept with corresponding learning materials class. The following pseudo code shows the Naïve Bayesian classifier algorithm based on (Sathyadevan et al. 2014).

Algorithm 1. Naïve Bayesian Classifier Algorithm

1. **Given training dataset X which consists of learning concepts belonging to different class A and B.**
2. **Calculate the prior probability of class A= number of learning concepts of class A / total number of learning concepts.**
   Calculate the prior probability of class B= number of learning concepts of class B / total number of learning concepts.
3. **Find n_i, the total number of learning concepts frequency of each class.**
   n_a= the total number of learning concept frequency of class A.
   n_b= the total number of learning concept frequency of class B.
4. **Find conditional probability of learning concept occurrence given a class.**
   P(X $_1$ / class A) = learning concept count / n_i (A)
   P(X $_1$ / class B) = learning concept count / n_i (B)
   P(X $_2$ / class A) = learning concept count / n_i (A)
   P(X $_2$ / class B) = learning concept count / n_i (B)
   ....
   ....
   P(X $_n$ /class B) = learning concept count / n_i (B)
5. **Avoid zero frequency problems by applying uniform distribution.**
6. **Classify a new learning concept X based on the probability P(X/C).**
   a) **Find P(Class A / X) = P(Class A) * P(X $_1$ / class A) * P(X $_2$ / class A)......* P(X $_n$ /class A).**
   b) **Find P(Class B / X) = P(Class B) * P(X $_1$ / class B) * P(X $_2$ / class B)......* P(X $_n$ /class B).**
7. **Assign learning concept to the class that has higher probability.**

The second phase related to test if the learning conceptx_1 through $x_n$learning concepts related to the learning materials class, $C_K$or not. In general case, given the learning concept classes C_K and a set of learning concepts X_i want to be classified, represented by a vector $X_i = (x_1 , x_2 , \ldots\ldots , x_n)$ to some n learning concepts. By using the Baye's theorem, the equation of conditional probability can be formulated as (Stokes et al. 2014):

$$P(C_K|x_i) = \frac{P(C_K)P(x_i|C_K)}{P(x_i)} \qquad (1)$$

Where:

- $P(C_K|x_i)$ is the posterior probability of learning concept class (target) given learning concept (feature) .
- $P(C_K)$ is the prior probability of learning concept class.
- $P(x_i|C_K)$ is the likelihood which is the probability of learning concept given learning concept class.
- $P(x_i)$ is the prior probability of learning concept.

By using the Bayesian probability terminology, the previous equation can be written as:

Posterior = (Prior * Likelihood) / Evidence

The expression for the probability that C_K will take on its all possible values, According to Bayes rule:

$$P(C_K|X_1 \ldots X_n) = \frac{P(C_K)\ P(X_1 \ldots X_n \,|\, C_K)}{\sum_j P(C_K)\ P(X_1 \ldots X_n \,|\, C_K)} \qquad (2)$$

Where the sum is taken all possible values of C. For all learning concepts $X_i = (x_1, x_2, \ldots\ldots, x_n)$ related to the learning materials class C_K, under the naive independence assumptions, equation (2) is used to rewrite it as:

$$P(C_K|X_1 \ldots X_n) = \frac{P(C_K)\ \prod_i P(X_i \,|\, C_K)}{\sum_j P(C_K)\ \prod_i P(X_i \,|\, C_K)} \qquad (3)$$

This means that the conditional distribution over the class variable C is:

$$P(C_K|X_1 \ldots X_n) = \frac{1}{Z} P(C_K) \prod_{i=1}^{n} P(X_i \,|\, C_K) \qquad (4)$$

where the evidence $Z = P(X) = \sum_j P(C_K)\ P(X_i \,|\, C_K)$ is a factor dependent on $(x_1, x_2, \ldots\ldots, x_n)$.

On the other hand, the naive Bayes classifier combines the independent assumptions with one of the famous common decision rules which is Maximum A Posterior (MAP) rule, so a Naive Bayesian Classifier equation can be written as follow (Cheeseman et al. 1988; Murphy 2006; Langley et al. 1992; Zhang 2004a; Vikramkumar et al. 2014):

$$P(C_K|x_i) = \mathrm{argmax}_{k \in \{1,\ldots,K\}}\, P(C_K) \prod_{i=1}^{n} p(x_i|C_K) \qquad (5)$$

Furthermore, the Naïve Bayesian use the Maximum A Posterior (MAP) decision rule to estimate $P(C_K)$ and $P(x_i|C_K)$ variables based on the frequency of learning concept in each learning materials class C_K in the training dataset (Zhang 2004b). Figure 7 show An example of naive Bayes Classifier.

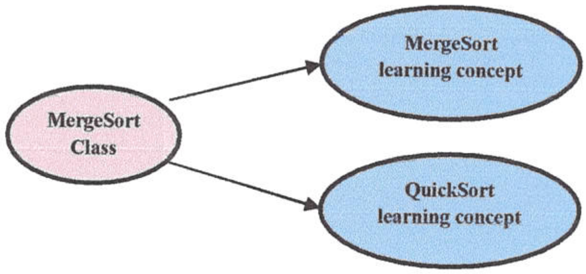

Figure 7: An example of Naive Bayes Classifier

The following example illustrates the Naive Bayesian classifier algorithm. As indicated, given the learning materials classes (*Introduction Class, MergeSort Class, QuickSort Class, Heaps Class, Hash Tables Class, Bloom Filters Class... etc*) and a set of learning concepts (*MergeSort, QuickSort*) want to be classified. Here, the inputs to the algorithm will be the learning concepts names that have been selected for reading by the learner. These inputs are divided into tokens in a process called tokenization process so that each token refers to a single word. After that, The resulting tokens are entered into the training phase of Naive Bayesian algorithm with the learning materials classes. In the Naive Bayesian testing phase, to determine any learning materials class associated with learning concept "*MergeSort*", initially, the frequency of learning concepts in each learning materials class are calculated as shown in the following Table 4:

Table 4: Frequency Table

		x_1	x_2
		MergeSort	**QuickSort**
c_1	**Introduction Class**	**5 times**	**3 times**
c_2	**MergeSort Class**	**20 times**	**6 times**
c_3	**QuickSort Class**	**10 times**	**15 times**
c_4	**Heaps Class**	**3 times**	**0 times**
		38 times	**24 times**

After that, the likelihood of the learning concepts in each learning material class are calculated as shown in the following Table 5:

Table 5: likelihood Table

		x_1	x_2	
		MergeSort	**QuickSort**	
c_1	**Introduction Class**	**5 / 38**	**3 / 24**	**8 / 62**
c_2	**MergeSort Class**	**20 / 38**	**6 / 24**	**26 / 62**
c_3	**QuickSort Class**	**10 / 38**	**15 / 24**	**25 / 62**
c_4	**Heaps Class**	**3 / 38**	**0**	**3 / 62**
		38 / 62	**24 / 62**	

Thus, can write:

$P(\boldsymbol{x_1}) = P(\boldsymbol{MergeSort}) =$ 38 / 62 = **0.6129 .**

$P(\boldsymbol{x_1}|\boldsymbol{c_1}) = P(\boldsymbol{MergeSort}|\boldsymbol{Introduction\ Class}) =$ 5 / 38 = **0.132** .

$P(\boldsymbol{c_1}) = P(\boldsymbol{Introduction\ Class}) =$ 8 / 62 =**0.129 .**

By using Baye's theorem equation, the posterior probability of learning concept "$\boldsymbol{MergeSort}$"to first learning materials class "$\boldsymbol{Introduction\ Class}$"is calculated as follows :

$$P(\boldsymbol{c_1}|\boldsymbol{x_1}) = P(\boldsymbol{Introduction\ Class}|\boldsymbol{MergeSort}) =$$

$$\frac{\boldsymbol{P(Introduction\ Class)P(MergeSort|Introduction\ Class)}}{\boldsymbol{P(MergeSort)}}$$

= **(0.129 * 0.132) / 0.6129 =0.02778 .**

Accordingly, all previous calculations are repeated to calculate all posterior probabilities for each learning concept in each learning materials class. After that, the equation of the Naïve Bayesian Classifier is applied to return the Maximum posterior probability value, which refers to the learning materials class that are related to the learning concept.

As a result of applying the previous phases, all learning concepts will be mapped to associated learning materials class. Thus, the first main process of the Naive Bayesian algorithm has been implemented as elaborated in figure 8.

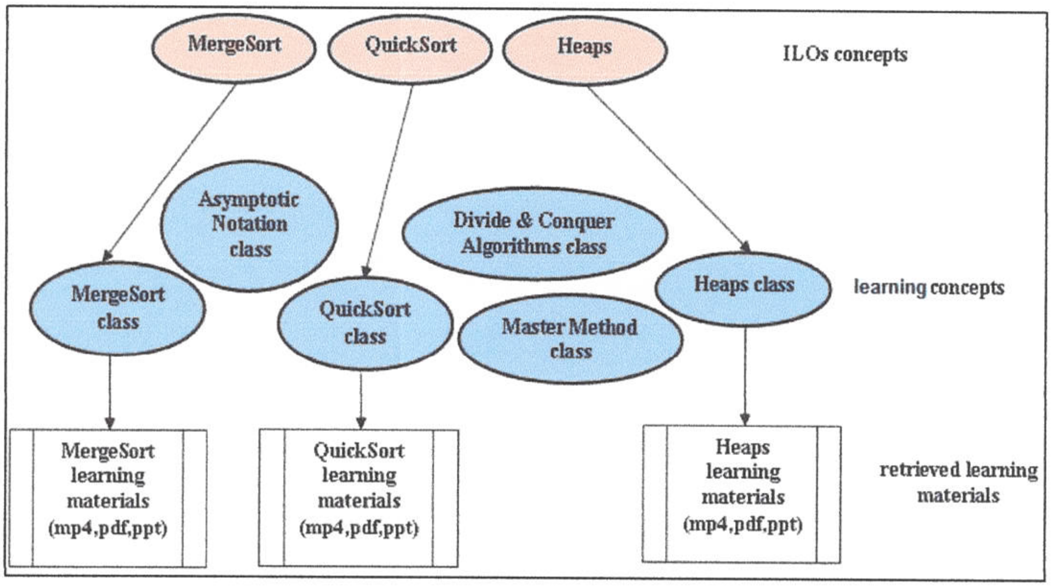

Figure 8: Mapping between the learning concepts of both ILOs and learning materials

Another aspect of the Naive Bayesian algorithm is to retrieve recommended resources to enhance learner's knowledge and to enable him to learn more about the learning concepts of the selected ILOs. A recommended resource is a learning material from different courses subjects that are related to the required learning concepts. This aspect was implemented by conducting some modification to the Naive Bayesian algorithm.

As mentioned above, the Naive Bayesian classifier algorithm output only one highest value of posterior probability at a time. This value is related to the learning materials class that contains the learning materials of learning concept from the subject at one course. These learning materials are presented to the learner until they are studied to master the learning concept.

Furthermore, to retrieve the recommended resources, an update to the algorithm was done in two steps: First, exception the learning materials class with the highest posterior probability value from the learning materials classes in training phase of the Naive Bayesian algorithm. Consequently, the algorithm does not retrieve the same learning materials that are related to the learning concept as a recommended resources. Second, the Naive Bayesian algorithm is recalled again. But here, the inputs to the algorithm will be the learning concept name and the name of the learning material that has been selected for reading by the learner. These inputs are divided into tokens in a process called tokenization process so that each token refers to a single word. After that, The resulting tokens are entered into the training phase of the Naive Bayesian algorithm with the learning materials classes.

In the Naive Bayesian testing phase, to determine any learning materials of learning materials classes associated with learning concept and open learning material, the frequencies of tokens in each learning materials class are calculated. Then, the likelihoods of tokens in each learning materials classes are calculated. After that, the Baye's theorem equation is applied to calculate the posterior probabilities of these tokens in each learning materials classes. Finally, the Naive Bayesian equation is applied to return the highest posterior probability value. So that the learning material related to this value is presented as a recommended resource for the learner.

It is important to mention that retrieving one recommended resource is not sufficient to support the knowledge of the learner. Therefore, the proposed system invokes the Naive Bayesian Classifier three times to introduce three recommended resources. This is not limited to three recommended resources. However, based on the adjustment more recommended resources can be provided if required by the instructor. Another important point here should be mentioned is that a textual information about the video files have been generated out of the attached caption of each lecture.

As a result of applying the previous steps, both learning materials and recommended resources that relate to selected learning concept have been adapted and presented to the learner. Thus, the second main process of the Naive Bayesian algorithm has been implemented.

Moreover, as the first phase of the proposed system, the learning path that must be followed by the learner will be generated and presented to the learner. Additionally, the learning style that is determined by the learner in learner profile (mp4, pdf, ppt) is taken into account when retrieving the learning materials. Therefore, the learning materials and recommended resources that take the same learning style are displayed for the learner.

Furthermore, after the learner completes all learning materials for each learning concept, the system offers assessments to evaluate the learner understanding of each learning concept. So that, If the learner does not exceed assessment threshold score, then the system represents the learning materials that are related to the learning concept to be learned again. As well as, the recommended resources are presented to enhance the learning process. It is important to mention here that the mapping between the assessments and the learning concepts is done manually.

3.3 Summary

The purpose of this chapter was to present the conceptual framework. Furthermore, important principles that are considered in proposing the conceptual framework were presented. After that, a number of functional requirements that have been formulated for providing adaptation inside MOOCs were clarified. Also, the different models that are considered in the proposed framework were explained. Finally, the general overview of the proposed adaptive MOOCs system as well as the two phases that have been performed were presented in details.

CHAPTER 4

PROPOSED FRAMEWORK VALIDATION

This chapter presents the validation of the proposed adaptive MOOCs framework based on intended learning outcomes (ILOs) as follow: Section 4.1 introduces the prototype of the proposed system. Furthermore, the learning style functionality is presented in section 4.1.1. After that, section 4.1.2 presents the automatic mapping between ILOs and learning materials. Also, section 4.1.3 presents the adaptation aspects and the learning path. Finally, summarizes this chapter in section 4.2.

4.1 Prototype of The Proposed System

The prototype of the proposed system was implemented using Java programming language, NetBeans IDE 8.0.1 program and the SQL Navigator 6.2.1. Also, the experiment was conducted by using a PC with Core i3 CPU (2.5GHz) and (4 GB) RAM. And the operating system is Windows 7.

4.1.1 Learning Style Functionality

In order to motivate the learners, the proposed system allows the learner to determine the learning style (mp4, pdf, ppt) that is preferred for presenting the learning materials. This is done by selecting the type of learning style in the learner profile as seen in figure 9. Therefore, the learning materials that take the same learning style are displayed for the learner.

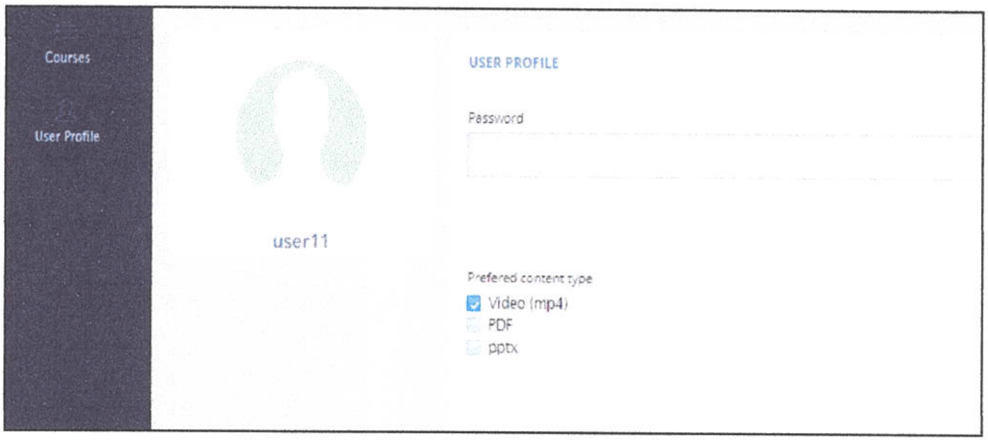

Figure 9: The learner profile

4.1.2 Automatic Mapping between ILOs and Learning Materials

As a preparation step of a case study of online courses to be used in the proposed system, two subjects have been selected: Data mining and Algorithms Design. Therefore, different learning materials have been collected from different courses in different MOOCs platforms. For instance, all learning materials from a course called "Algorithms Design and Analysis, Part 1" (from Coursera platform) have been downloaded to be used in the proposed solution.

Another phase in the preparation process is the identification of learning concepts in both learning materials and ILOs. Therefore, the lists of learning concepts for both ILOs and learning materials is done manually by determining the learning concepts that are related to both ILOs and learning materials. So that, each selected ILOs were mapped to one or several learning concepts. In addition, Each learning concept has one or more learning materials such as PDF, video lecture, and slides.

Categorizing the learning materials to a beginner, intermediate and advanced has been also done by experts in the manual matter. For example, the learning materials for each course have been classified and determine whether they are beginner, intermediate or advanced level through the labels that have been used to refer to them.

The learner will be able to start a course that fits his intended learning outcomes by following these steps: first, a learner needs to select the course subject as seen in figure 10. After that, a list of all possible ILOs for the selected course subject will be displayed as seen in figure 11. Second, the learner will select the ILOs that he would like to achieve after completing the course.

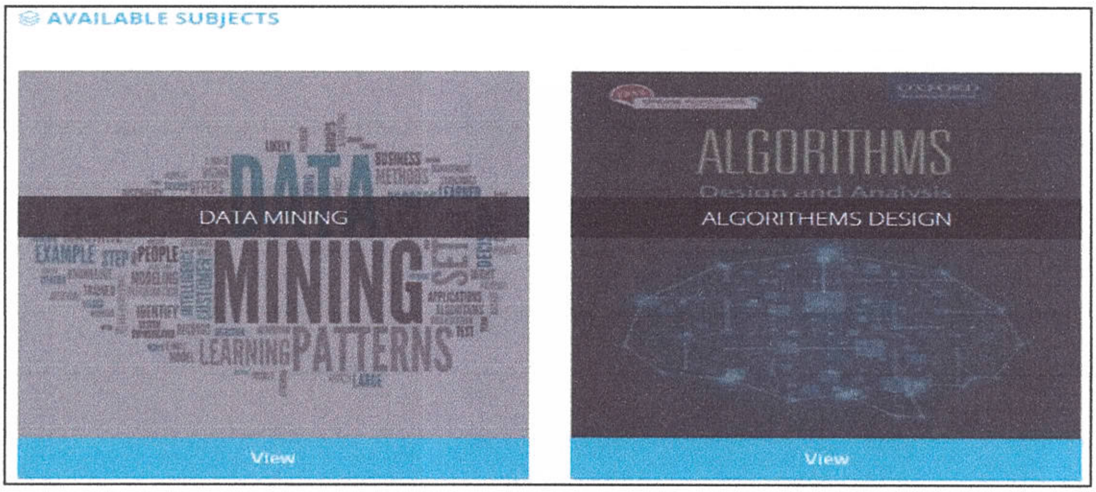

Figure 10: The available course subjects in the proposed system

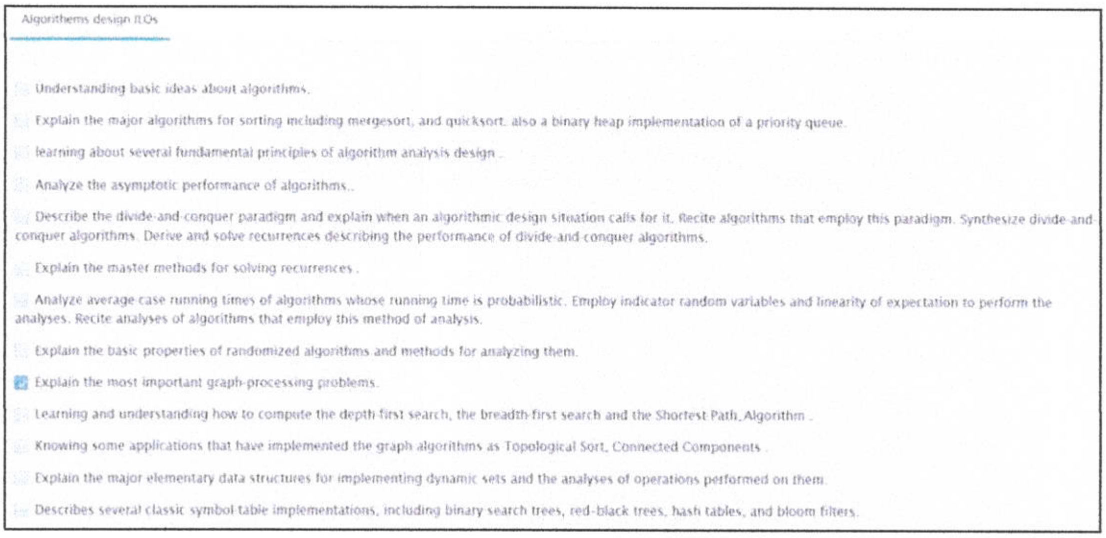

Figure 11: The list of related ILOs to selected course subject

From the above figure, let us assume that the learner selected the course subject *"ALGORITHEMS DESIGN"* and selected also the following ILOs among a list of related ILOs:1- *"Explain the major algorithms for sorting including mergesort, and quicksort, also a binary heap implementation of a priority queue"*, 2-*"Explain the most important graph-processing problems"*, and 3-*"Study and implement the Minimum spanning tree as an application to Clustering"* as shown in the figure 12.

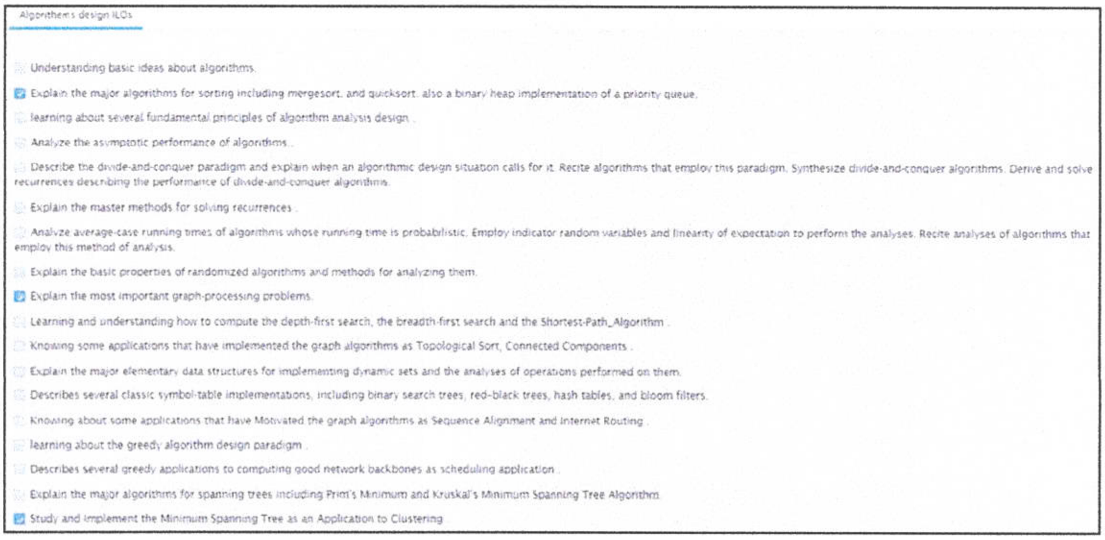

Figure 12: The selected ILOs that meet the learner needs.

Accordingly, the generated course will cover only the learning concepts that are mapped to the selected ILOs. Therefore, the learning concepts that will be covered in above example are: *"mergesort"* **learning concept**, *"quicksort"* **learning concept** and *"heap"* **learning concept** are mapped to *"Explain the major algorithms for sorting including mergesort, and quicksort, also a binary heap implementation of a priority queue"* **ILO**. Also, *"Graphs and the contraction algorithms"* **learning concept** is mapped to *"Explain the most important graph-processing problems"* **ILO**. And *"Clustering"* **learning concept** is associated to the *"Study and implement the Minimum spanning tree as an application to Clustering"* **ILO**. The learning concepts that are identified in this step are the result of employing the adaptation rules as follows:

- IF **ILO selected**: "Explain the major algorithms for sorting including mergesort, and quicksort, also a binary heap implementation of a priority queue"
  THEN **Add learning concept** "mergesort", **learning concept** "quicksort" and the **learning concept** "heap" to the list of learning concepts.
- IF **ILO selected**: "Explain the most important graph-processing problems"
  THEN **Add learning concept** "Graphs and the contraction algorithms" to the list of learning concepts.
- IF **ILO selected**: "Study and implement the Minimum spanning tree as an application to Clustering" THEN **Add learning concept** "Clustering" to the list of learning concepts.

Moreover, the previous learning concepts have predefined pedagogical relationships (defined in the Pedagogical model) as follows:

- Mergesort ***illustrates*** sorting algorithm .

- Quicksort ***illustrates*** sorting algorithm.
- Heap ***illustrates*** sorting algorithm .
- Mergesort is ***prerequisite*** Quicksort.
- Quicksort is ***prerequisite*** Heap.
- Graphs and the contraction algorithms ***illustrates*** graph-processing problems.
- Minimum spanning tree ***defines*** Clustering.

4.1.3 Adaptation Aspect and Learning Path

As a result of the previous section, the learning materials that are associated with each selected learning concepts are presented. Thus, the learner can start reading and viewing the learning materials by following the sequence of the learning materials that has been identified by experts. So that, the learner cannot move from the first learning material to the second learning material until he opens it. For instance, the learning materials of the *"Mergesort"* **learning concept** are offered for the learner as elaborated in figure 13.

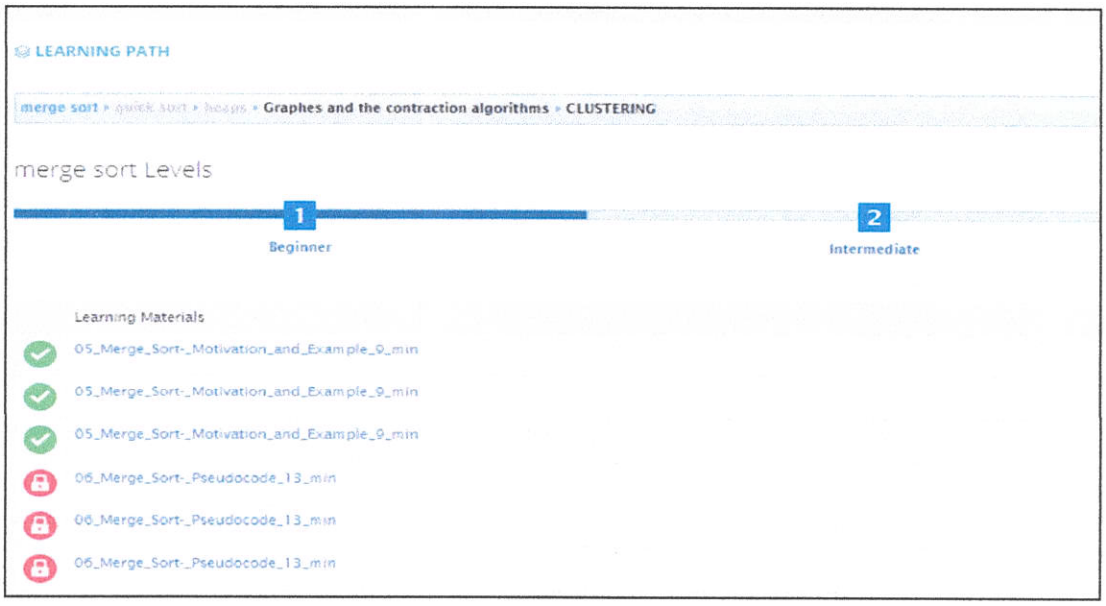

Figure 13: The learning materials of selected learning concept .

Moreover, when the learner opens a learning material for reading or viewing, the learning material is presented taking into account the learning style that was determined by the learner as shown in figure 14.

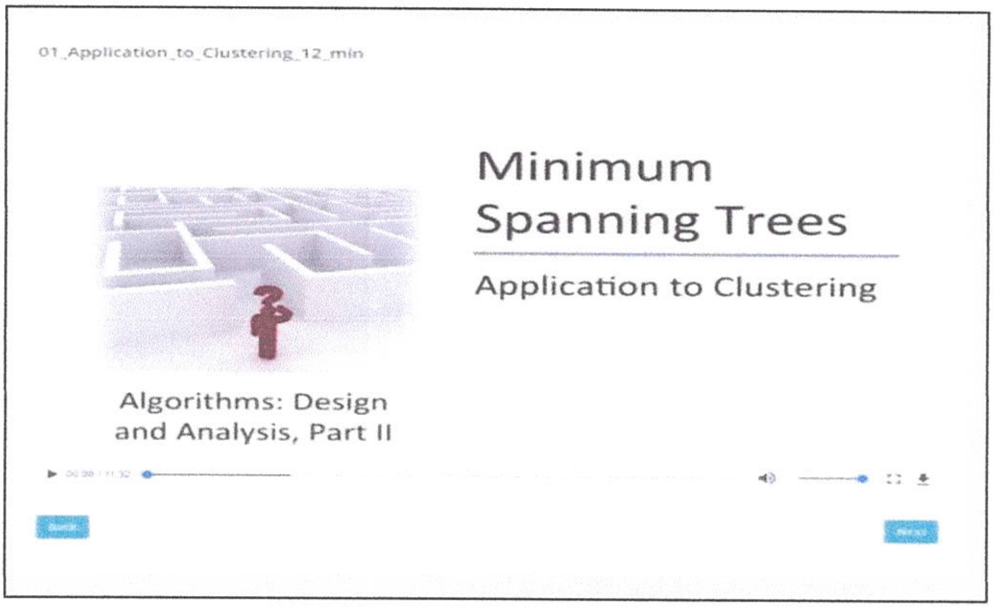

Figure 14: Presented learning material with selected learning style (.mp4)

Additionally, Three of recommended resources are presented to the learner in order to enhance the learner's knowledge and enable him to learn more about the learning concept as elaborated in figure 15.

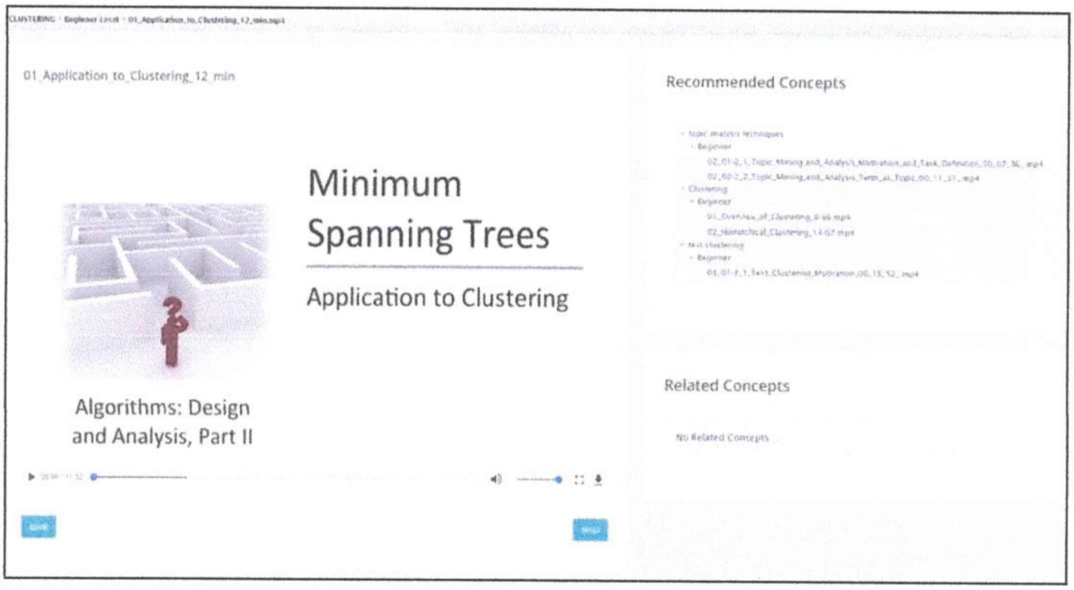

Figure 15 : Related recommended resources

On the other hand, the learning path that must be followed by the learner during the learning process is generated based on the pedagogical relationships between the learning concepts. And then displayed it for the learner as seen in figure 16. So that, the learner cannot move from learning concept to another if it is based on a previous learning concepts that have not been completed yet. For example, the learning materials of the *"Quicksort"* **learning concept** will not be presented until all learning materials of *"Mergesort"* **learning concept** have been completed. Because of a " ***prerequisite*** " pedagogical relationship between the two learning concepts as seen in figure 17.

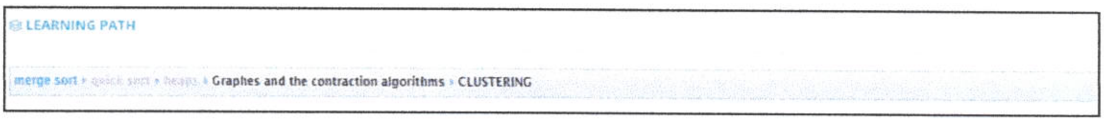

Figure 16: The learning path for the selected ILOs concepts.

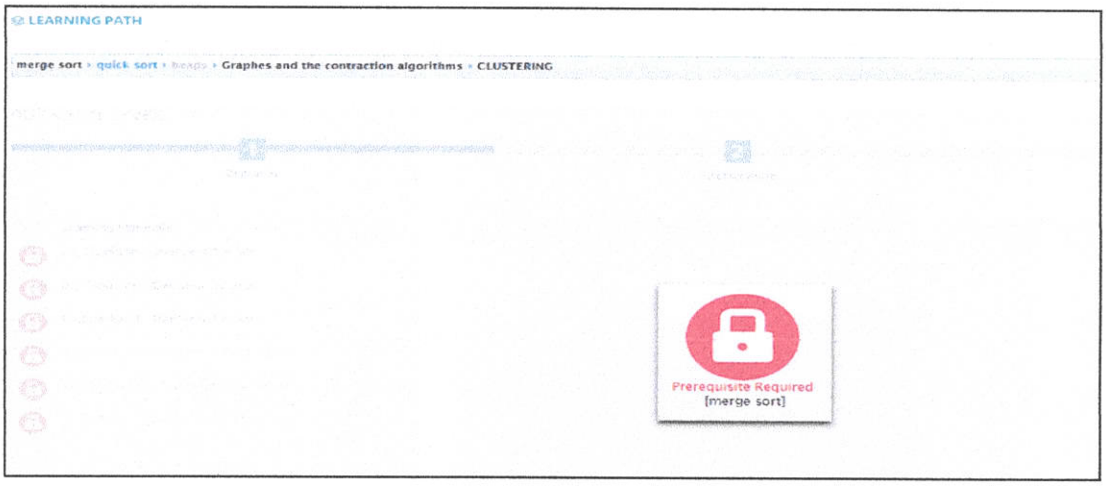

Figure 17: the pedagogical relationships between the learning concepts

Note that the learning concepts appeared in different colors in the learning path. These colors enable the learner to know the situation that has been accessed for each learning concept during the learning process. This system identifies four different situations which are: first, learning concepts that have been read and completed. Second, learning concepts based on previous learning concepts. Third, learning concepts that are currently reading and the last situation is the learning concepts that have not been open yet. Thus, each color refers to a specific situation as follows:

- Dark blue color: the learner read and completed this learning concept.
- Gray color: the learning concept is based on previous learning concept that must be completed.
- Light blue color: the learner reads this learning concept now.
- Black color: the learning concept is not yet open.

After completing of opening and reading all learning materials that are related to a particular learning concept, the proposed system presents the assessment associated with that learning concept for the learner as clarified in figure18.

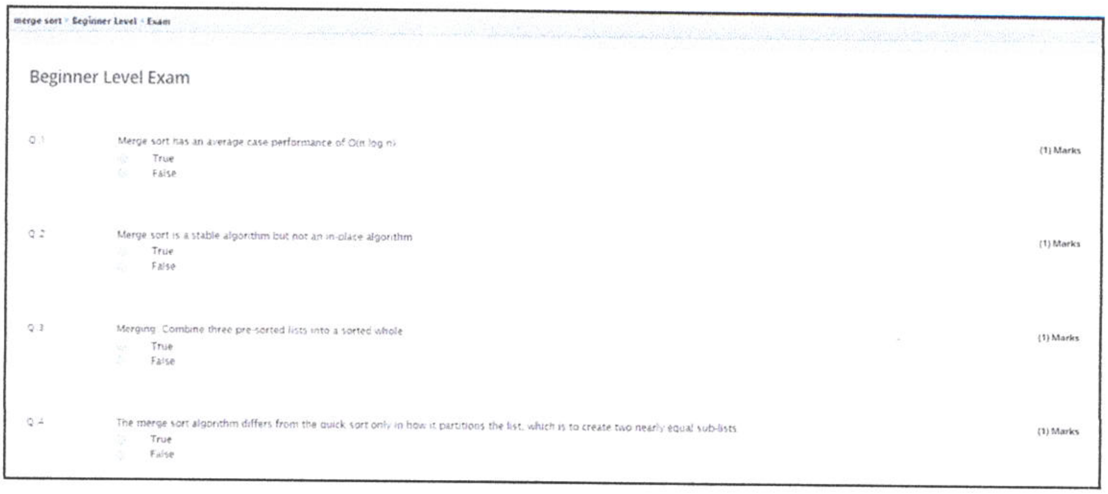

Figure 18: assessment that are related to mergesort learning concept

Therefore, If the learner has passed the success mark, then the learning concept color is changed to dark blue color to be completed and the learner can move to other learning concepts as seen in figure 19.

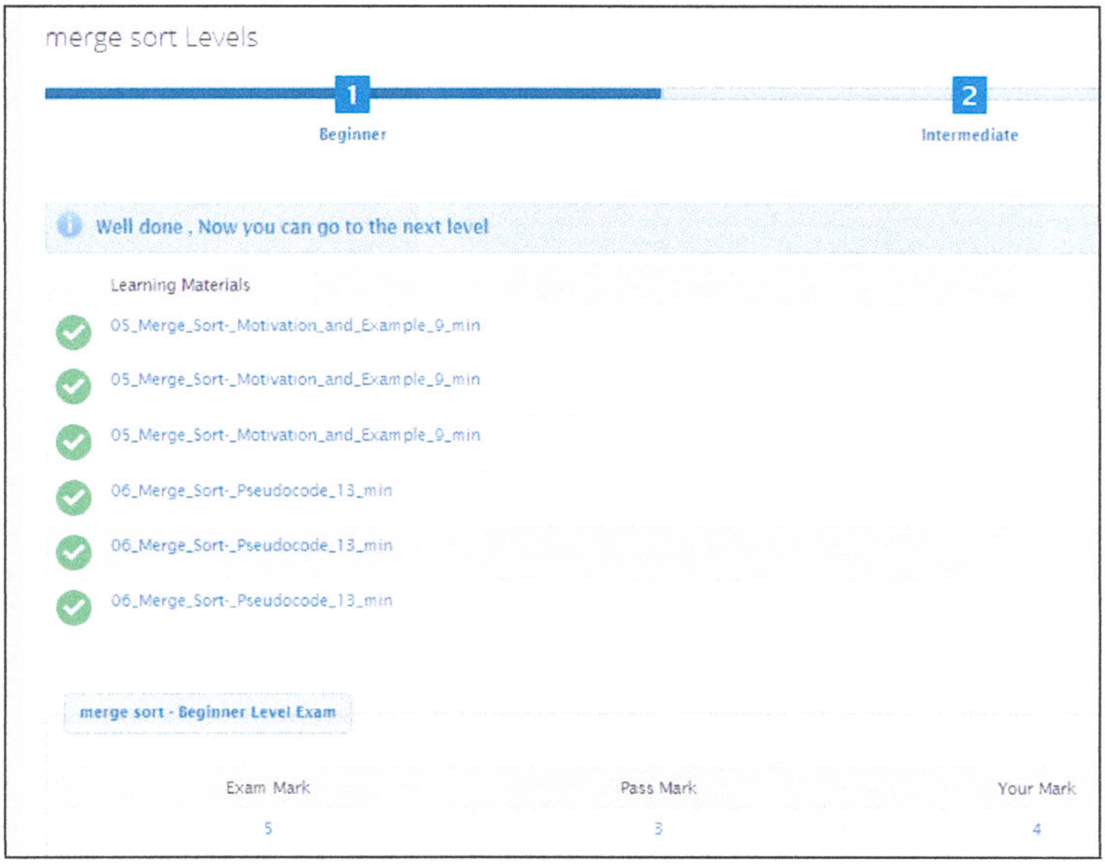

Figure 19: The learner succeeded and could move to next learning concept

Otherwise, the same learning materials that are related to the learning concept are re-introduced for the learner to be learned again. In addition, a report of the wrong-answer questions is presented to the learner so that the learner is able to identify his/her weaknesses in the learning materials of the learning concept as seen in figure 20.

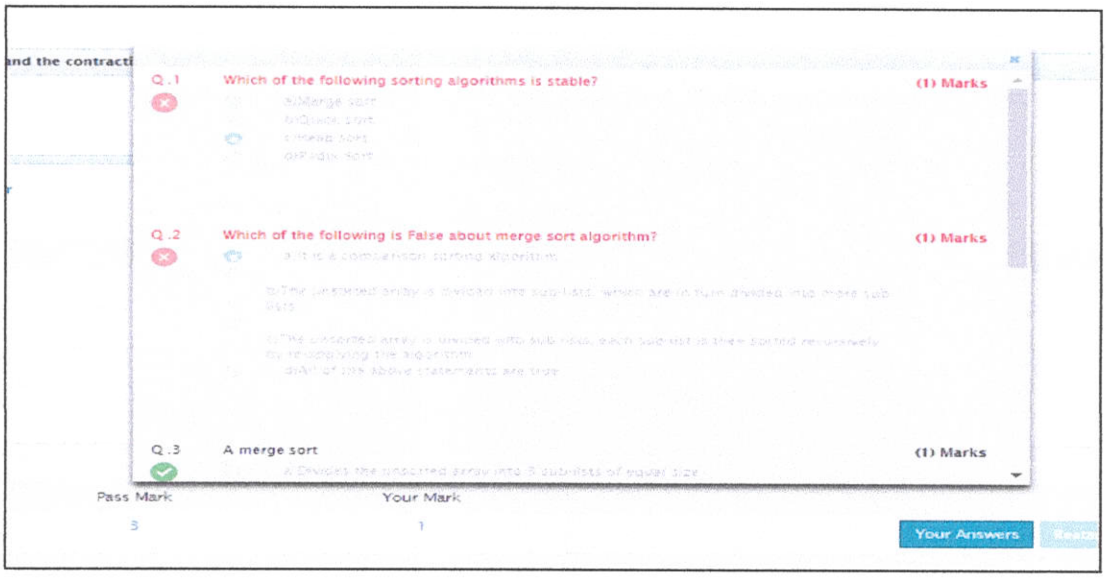

Figure 20: The wrong-answer questions report

4.2Summery

The purpose of this chapter was to present the prototype of the proposed adaptive MOOCs system based on intended learning outcomes (ILOs). In beginning, the learning style functionality was presented. After that, the automatic mapping between learning materials and ILOs was illustrated. Finally, the adaptation aspects and the learning path were explained.

CHAPTER 5

EXPERIMENTAL EVALUATION

This chapter illustrates the experiment that has been conducted to evaluate the Adaptive MOOCs system. The evaluation has been carried out in three stages. the first stage evaluates the proposed system by using the Precision and Recall indicators in order to estimate the effectiveness when utilizing the Naive Bayesian Classifier technique in the matching process between the ILOs, learning materials and in recommending new learning resources. The second stage of the evaluation is a descriptive analysis has been performed to a set of questionnaires has been filled out by six learners who have experimented the proposed system. This questionnaire covers four major points of system performance that will be analyzed in details. In the last stage of evaluation, the proposed work has been evaluated by five educators in several aspects, such as the added value of the recommendation of new learning resources, the adaptive learning path in order to meet the learning outcomes that he wants to learn.

The rest of this chapter is organized as follows. Section 5.1 presents the first stage of the system evaluation. The second stage of the experimental evaluation is discussed in section 5.2. Additionally, section 5.3 shows the last stage of the system evaluation. Also, section 5.4 introduces the discussion of the evaluation results. Finally, summarizes this chapter in section 5.5.

5.1 The First Stage of Experiment Evaluation

This section describes the experiment that was performed to evaluate the effectiveness of the proposed system. The effectiveness of the proposed system is evaluated based on how accurate in specifying process of relevance scores between Intended Learning Outcomes (ILOs) and their corresponding learning materials and recommended resources (learning materials and recommended resources that have been retrieved by the system). To achieve this task, we have carried out the experiment on a dataset that consists of numbers of online free coursera courses[2] and 48 different intended learning outcomes (ILOs) obtained from downloaded courses syllabus. The dataset includes four courses covering two different subjects (data mining and algorithm design) with (1518) learning materials in different formats such as (.pdf, .mp4, .ppt).

In order to provide a basis for evaluating the quality of the system outcomes, the learning materials and ILOs have been matched manually in the first phase of the proposed system as well as all relevant potential judgments between the ILOs and their relevant learning resources have been specified. The previous judgments were built based on the knowledge and experience of relevance educators to courses available in the dataset. Then, the results of the manually specified relevance scores were compared with those results that were automatically produced in the second phase of the proposed system. So that, the Precision/Recall (P/R) indicators were utilized to measure the quality of the obtained outcomes of the second phase where (Manning et al. 2009) :

[2]Some courses downloaded from (http://academictorrents.com/browse.php) which is named (Algorithms Design and Analysis, Part 1, Algorithms Design and Analysis, Part 2, mining massive dataset and Text Mining and Analytic Course).

$$P = \frac{|relevantlearningresources| \cap |retrieved\ learning\ resources|}{|retrieved\ learning\ resources|} \quad (6)$$

$$R = \frac{|relevantlearningresources| \cap |retrieved\ learning\ resources|}{|relevant\ learning\ resources|} \quad (7)$$

For instance, to calculate the Precision/Recall (P/R) indicators for ILO's "*Explain the most important graph-processing problems*", we need to calculate the following:

First, it calculates the number of learning resources that are relevant to the learning concept *"Graphes and the contraction algorithms"*, and their number is (39 learning materials).

Second, it calculates the number of learning resources that are retrieved to the learning concept *"Graphes and the contraction algorithms"* by the system during the learning process, and their number is (44 learning materials).

Third, it calculates the number of learning materials relevant to the learning concept "Graphes and the contraction algorithms" and have been retrieved by the system during the learning process,. The number of learning materials was (32 learning materials).

By applying the equations mentioned above, the results of the indicators are as follows:

P = (32 / 44) * 100% = 0.727 * 100 % $\cong$ 73 % .

R = (32 / 39) * 100% = 0.820 * 100 % $\cong$ 82 % .

Similarly, the process is repeated to calculate the Precision and Recall(P/R) indicators for the remaining ILO's .

The following table clarifies results for some Intended Learning Outcomes (ILOs) :

Table 6: Precision and Recall Results

ILOs	P	R
Explain the most important graph-processing problems	73%	82%
Explain the major algorithms for spanning trees including Prime's Minimum and Kruskal's Minimum spanning tree algorithm	80%	88%
Study and implement the Minimum spanning tree as an application to Clustering	71%	86%

As seen in table 6 ,we note that the precision indicator results range between 71% and 80% percent while the results of the recall indicator range between 82% and 88% percent. This means that the Naive Bayesian is able to do its work in terms of retrieving the learning materials and recommended resources based on selected Intended Learning Outcomes (ILOs) almost effectively when compatible it with the produced results of manual mapping.

There are many previous studies that have been used the Naive Bayesian Classifier algorithm for the classification texts and documents, but it is not used for the same purpose which has been used in this research work. The studies indicated that their results were characterized by a high accuracy. Moreover, it has the ability to work in a way that surpasses the most advanced classification models such as boosted trees or random forests models (Metsis et al. 2006; Rajeswari & Juliet 2017;Caruana & Niculescu-Mizil, 2006;Zhu et al., 2017; Rish 2001;Yoo et al. 2016). However, a comparison with such research is not fair as they have been used in different contexts.

5.2 The Second Stage of Experiment Evaluation

This stage evaluated the adaptive MOOC system based on intended learning outcomes (ILOs) by analyzing the results of a questionnaire given to six learners who have experimented the proposed system. More details about the questionnaire is presented in Appendix A.

The proposed questionnaire consists of four main aspects. The first aspect relates to some basic data about participants and the use of e-learning applications. The second aspect is focused on the quality of the provided courses and measure the system usability by the learners. On the other hand, the third aspect consists of 20 questions about the acceptability of the proposed system as well as clarifying the learners impression after experiencing the system. Finally, the perceived workload while learning and working with MOOC courses will be measured through learners answers on the remaining questions. The descriptive analysis is done through tables and figures in Appendix B.

5.2.1 Demographic Questionnaire for Learners (DQL)

Table 7 : Learn from the Internet and use learning applications

	Never	Less frequently than once a week	Several times a week	Daily
How often do you learn from the internet in general?	0.00	16.67	83.33	0.00
How often do you use e-learning applications (including coursera, udemy, edx, etc.)?Please choose only one of the following:	0.00	83.33	16.67	0.00

As we seen, table 7 presents an individual sample measuring the extent to which the internet is used in learning. we found that the answers and the percentage ranged between Less frequently than once a week (minimum value) with **16.7%** percent and several times a week (maximum value) with **83.3%** percent in where the mode and the median of their answers are, several times a week.

The same table shows an individual sample measuring the usage of e-learning applications by the learners. we found that the answers and the percentage ranged between less frequently than once a week (minimum value) with **83.3%** percent and several times a week (maximum value) with **16.7%** percent. in which the mode and the median of their answers are, less frequently than once a week.

5.2.2 Usability - System Usability Scale (SUS)

Table 8 :System Usability Scale (SUS)- Percentage frequency

	Usability - System Usability Scale (SUS)	Percentage frequency				
		strongly disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	strongly agree (5)
1	I think that I would like to use the adaptive MOOC course.	0.00	0.00	0.00	83.33	16.67
2	I found the Adaptive MOOC course is unnecessarily complex.	16.67	33.33	16.67	0.00	33.33
3	I think the adaptive MOOC is easy to use.	0.00	0.00	0.00	66.67	33.33
4	I think that I would need the support of a technical person to be able to use this Course in the future.	33.33	50.00	16.67	0.00	0.00
5	I found the various parts in this adaptive MOOC course were well integrated.	0.00	0.00	0.00	83.33	16.67
6	I think there is too much inconsistency in this Course.	16.67	50.00	33.33	0.00	0.00
7	I would imagine that most of my classmates would learn to use this Course very quickly.	0.00	0.00	0.00	83.33	16.67
8	I found the adaptive MOOC Course very cumbersome to use.	50.00	33.33	0.00	16.67	0.00
9	I felt very confident using the adaptive MOOC Course.	0.00	0.00	0.00	66.67	33.33
10	I needed to figure out a lot of things before I could get going with this Course.	33.33	33.33	0.00	0.00	33.33
11	I would like to use this adaptive Course in the future.	0.00	0.00	0.00	66.67	33.33
12	I would recommend this adaptive course to my colleagues.	0.00	0.00	0.00	16.67	83.33

Table 9 :System Usability Scale (SUS) -Mean and St.dev

	Usability - System Usability Scale (SUS)	Mean	St.dev
1	I think that I would like to use the adaptive MOOC course.	4.17	0.41
2	I found the Adaptive MOOC course is unnecessarily complex.	3.00	1.67
3	I think the adaptive MOOC is easy to use.	4.33	0.52
4	I think that I would need the support of a technical person to be able to use this Course in the future.	1.83	0.75
5	I found the various parts in this adaptive MOOC course were well integrated.	4.17	0.41
6	I think there is too much inconsistency in this Course.	2.17	0.75
7	I would imagine that most of my classmates would learn to use this Course very quickly.	4.17	0.41
8	I found the adaptive MOOC Course very cumbersome to use.	1.83	1.17
9	I felt very confident using the adaptive MOOC Course.	4.33	0.52
10	I needed to figure out a lot of things before I could get going with this Course.	2.67	1.86
11	I would like to use this adaptive Course in the future.	4.33	0.52
12	I would recommend this adaptive course to my colleagues.	4.83	0.41

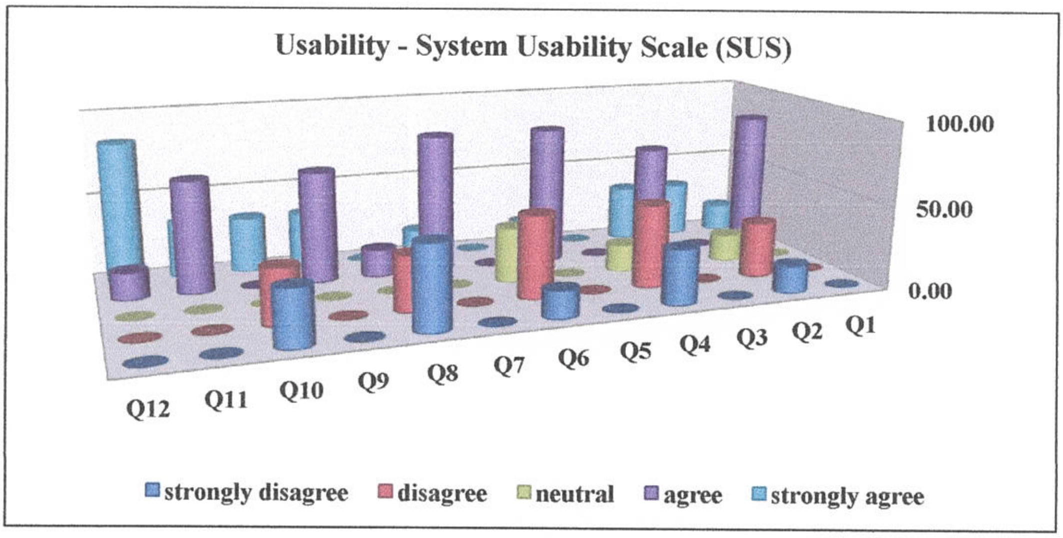

Figure 21: System Usability Scale (SUS)

As we seen in table 8, table 9 and figure 21, we can conclude the following:

1. The extent of learner's preference for using of Adaptive MOOCs system ranges between value **4** which is the minimum value with percentage of **83.3%** (agree) and the maximum value **5** with percentage of **16.7%** (strongly agree) in which the mode and the median of their answers are, the value **4** (agree) .

2. The learners opinion about whether the adaptive MOOCs course system is unnecessarily complex or not. We found that there was a great variation in the learners answers ranged between value **1** (strongly disagree) which is the minimum value with percentage of **16.7%** and value **5** (strongly agree) which is the maximum value with percentage of **33.3%**. In this context, there are two modes (two and five) that provide an evidence of variation in learners answers. As for the median, it is equal **2.5** which is close to **3** (neutral) .
3. The learners opinion about whether the adaptive MOOCs course system is easy to use or not. We found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **66.7%** and the maximum value **5** (strongly agree) with percentage of **33.3%** in which the mode and the median of their answers are, the value **4** (agree).
4. The learners opinion about whether they need to support a technical person when using the Adaptive MOOCs course in the future or not. we found that the answers and the percentage ranged between value **1** (strongly disagree) which is the minimum value with percentage of **33.3%** and the maximum value **3** (neutral) with percentage of **16.7%**. In addition, the mode and the median are the value **2** (disagree) which is the answer of the most learners.
5. The learner answers for founding the various parts in adaptive MOOC course were well integrated ranges between value **4** (agree) which is the minimum value with percentage of **83.3%** and the maximum value **5** (strongly agree) with percentage of **16.7%** in where the mode and the median of their answers are, the value **4** (agree).

6. The learners opinion about there is too much inconsistency in adaptive MOOC course ranges between value **1** (strongly disagree) which is the minimum value with percentage of **16.7%** and the maximum value **3** (neutral) with percentage of **33.3%** in where the mode and the median of their answers are, the value **2** (disagree).
7. The point of view of learners about imagining that most of their classmates will learn to use adaptive MOOC course very quickly ranges between value **4** (agree) which is the minimum value with percentage of **83.3%** and the maximum value **5** (strongly agree) with percentage of **16.7%**.in where the mode and the median of their answers are, the value **4** (agree).
8. The learners opinion about founding the adaptive MOOC Course very cumbersome to use ranges between value **1** (strongly disagree) which is the minimum value with percentage of **50%** and the maximum value **4** (agree) with percentage of **16.7%** in where the mode and the median of their answers are, the value **2**. In where the mode is equal value **1** (strongly disagree) and the median of their answers are the value **1.5** which is close to **2** (disagree) .
9. The point of view of learners about feeling confident when using the adaptive MOOC Course ranges between value **4** (agree) which is the minimum value with percentage of **66.7%** and the maximum value **5** (strongly agree) with percentage of **33.3%** in where the mode and the median of their answers are, the value **4** (agree).
10. The learners opinion about whether they need to figure out so many things before they could explore the proposed adaptive MOOC course or not. we found that the

answers and the percentage ranged between value **1** (strongly disagree) which is the minimum value with percentage of **33.3%** and the maximum value **5** (strongly agree) with percentage of **33.3%** in where there are three modes for this variable are **1**, **2** and **5** but the median of their answers are, the value **2** (disagree).

11. The learners opinions about using adaptive MOOCs Course system in the future ranges between value **4** (agree) which is the minimum value with percentage of **66.7%** and the maximum value **5** (strongly agree) with percentage of **33.3%** in where the mode and the median of their answers are, the value **4** (agree) .
12. The answers of learners about if they would recommended this adaptive MOOCs system to their colleagues ranges between value **4** (agree) which is the minimum value with percentage of **16.7%** and the maximum value **5** (strongly agree) with percentage of **83.3%**.in where the mode and the median of their answers are, the value **5** (strongly agree).

5.2.3 Acceptance: Subjective Impression Questionnaire (SIQ)

Table 10 : Subjective Impression Questionnaire (SIQ)-Percentage frequency

#	Acceptance: Subjective Impression Questionnaire (SIQ)	Percentage frequency				
		strongly disagree(1)	disagree (2)	Neutral (3)	agree (4)	strongly agree(5)
1	I would use the adaptive MOOC Course whenever possible.	0.00	0.00	0.00	66.67	33.33
2	I would use the adaptive MOOC Course frequently when it is available.	0.00	0.00	0.00	50.00	50.00
3	Using the adaptive course is a good idea.	0.00	0.00	0.00	0.00	100.00
4	Using the adaptive Course is unpleasant.	50.00	50.00	0.00	0.00	0.00
5	Using the adaptive MOOC Course would be beneficial to my learning.	0.00	0.00	0.00	66.67	33.33
6	Using the adaptive MOOC Course is easy for me.	0.00	0.00	0.00	50.00	50.00
7	It was easy for me to become skilful at using the adaptive MOOC Course.	0.00	0.00	0.00	33.33	66.67
8	I find the adaptive MOOC Course easy to use.	0.00	0.00	0.00	50.00	50.00

9	I find the adaptive MOOC Course to be flexible to interact with.	**0.00**	**0.00**	**0.00**	**66.67**	**33.33**
10	Integrating adaptive learning path helps me to understand learning concepts being studied.	**0.00**	**0.00**	**0.00**	**33.33**	**66.67**
11	Provided adaptation techniques within the Course is clear and understandable.	**0.00**	**0.00**	**0.00**	**66.67**	**33.33**
12	It is easy to know which part is required for more study using the provided adaptation techniques.	**0.00**	**0.00**	**0.00**	**50.00**	**50.00**
13	It is useful to navigate through course	**0.00**	**0.00**	**0.00**	**66.67**	**33.33**
14	Synchronization between ILOs and learning concepts draws your attention.	**0.00**	**0.00**	**33.33**	**33.33**	**33.33**
15	The provided adaptation techniques are needed for better understanding of a course (e.g. Algorithm course)	**16.67**	**0.00**	**16.67**	**50.00**	**16.67**
16	Providing related concepts part is useful	**0.00**	**0.00**	**0.00**	**50.00**	**50.00**
17	Providing recommended concepts part is useful	**0.00**	**0.00**	**0.00**	**50.00**	**50.00**
18	I used recommended learning concepts better understanding of a course (e.g. Algorithm course)	**0.00**	**0.00**	**0.00**	**50.00**	**50.00**
19	I used related learning concepts better understanding of a course (e.g. Algorithm course)	**0.00**	**0.00**	**0.00**	**66.67**	**33.33**
20	I prefer to follow a classical course without using the adaptive MOOC.	**50.00**	**33.33**	**0.00**	**16.67**	**0.00**

Table 11: Subjective Impression Questionnaire (SIQ)-Mean and St.dev

#	**Acceptance: Subjective Impression Questionnaire (SIQ)**	**Mean**	**St.dev**
1	I would use the adaptive MOOC Course whenever possible.	**4.33**	**0.52**
2	I would use the adaptive MOOC Course frequently when it is available.	**4.50**	**0.55**
3	Using the adaptive course is a good idea.	**5.00**	**0.00**
4	Using the adaptive Course is unpleasant.	**1.50**	**0.55**
5	Using the adaptive MOOC Course would be beneficial to my learning.	**4.33**	**0.52**
6	Using the adaptive MOOC Course is easy for me.	**4.50**	**0.55**
7	It was easy for me to become skilful at using the adaptive MOOC Course.	**4.67**	**0.52**
8	I find the adaptive MOOC Course easy to use.	**4.50**	**0.55**
9	I find the adaptive MOOC Course to be flexible to interact with.	**4.33**	**0.52**
10	Integrating adaptive learning path helps me to understand learning concepts being studied.	**4.67**	**0.52**
11	Provided adaptation techniques within the Course is clear and understandable.	**4.33**	**0.52**
12	It is easy to know which part is required for more study using the provided adaptation techniques.	**4.50**	**0.55**
13	It is useful to navigate through course	**4.33**	**0.52**

14	Synchronization between ILOs and learning concepts draws your attention.	**4.00**	**0.89**
15	The provided adaptation techniques are needed for better understanding of a course (e.g. Algorithm course)	**3.50**	**1.38**
16	Providing related concepts part is useful	**4.50**	**0.55**
17	Providing recommended concepts part is useful	**4.50**	**0.55**
18	I used recommended learning concepts better understanding of a course (e.g. Algorithm course)	**4.50**	**0.55**
19	I used related learning concepts better understanding of a course (e.g. Algorithm course)	**4.33**	**0.52**
20	I prefer to follow a classical course without using the adaptive MOOC.	**1.83**	**1.17**

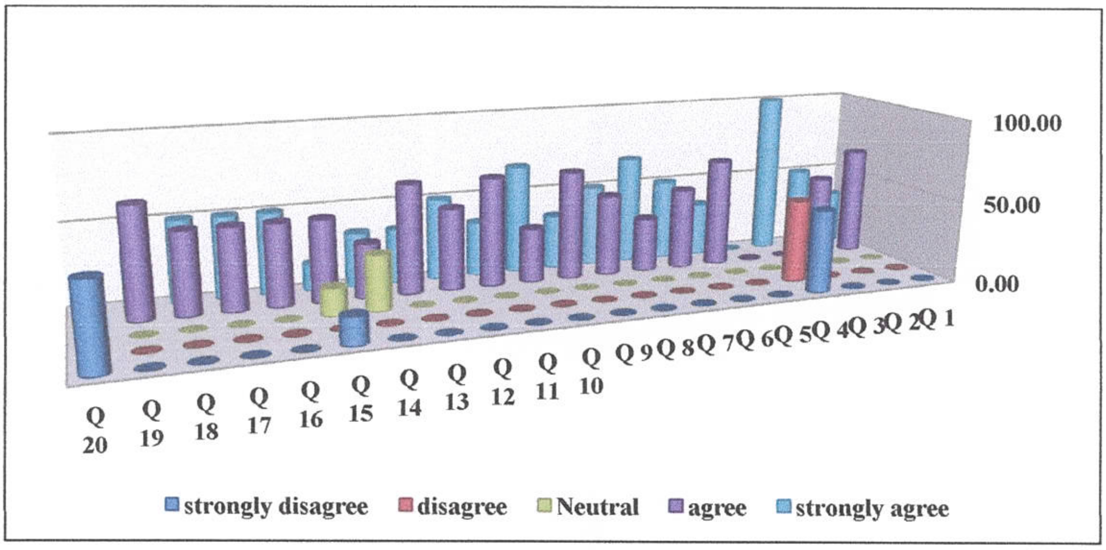

Figure 22: Subjective Impression Questionnaire (SIQ)

As we seen in table 10, table 11 and figure 22, we can conclude the following:

1. The learners opinion about using the adaptive MOOCs course system whenever possible. we found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **66.7%** and the maximum value **5** (strongly agree) with percentage of **33.3%** in which the mode and the median of their answers are, the value **4** (agree) .
2. The learners opinion about using the adaptive MOOCs course system frequently when it is available. we found that the answers and the percentage ranged between

value **4** (agree) which is the minimum value with percentage of **50%** and the maximum value **5** (strongly agree) with percentage of **50%** in which there are two modes (four and five) and the median of their answers are, the value **4** (agree).

3. The learners opinion about using the adaptive MOOCs course system is a good idea. we found that the answers of the participants are **5** (strongly agree), which means that the median and the mode also equal **5** (strongly agree).
4. The answers of learners about whether using the adaptive MOOC Course system is unpleasant or not. we found that the answers and the percentage ranged between value **1** (strongly disagree) which is the minimum value with percentage of **50%** and the maximum value **2** (disagree) with percentage of **50%** in where there are two modes (two and one) and the median of their answers are equal **1.5** which is close to **2** (disagree).
5. The answers of learners about whether using the adaptive MOOC Course system would be beneficial of learning or not. we found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **66.7%** and the maximum value **5** (strongly agree) with percentage of **33.3%** in where the modes and the median of their answers are value **4** (agree).
6. The answers of learners about whether using the adaptive MOOC Course system is easy for the learner or not. we found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **50%** and the maximum value **5** (strongly agree) with percentage of **50%** in

where there are two modes (four and five) and the median of their answers are equal **4.5** which close to **5** (strongly agree).

7. The answers of learners about whether easy for learner to become skilful at using the adaptive MOOC Course or not. we found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **33.3%** and the maximum value **5** (strongly agree) with percentage of **66.7%** in where the modes and the median of their answers are value **5** (strongly agree).
8. The answers of learners about if the system easy to use or not. we found that the percentage ranged between value **4** (agree) which is the minimum value with percentage of **50 %** and the maximum value **5** (strongly agree) with percentage of **50 %** in where there are two modes (four and five) and the median of their answers are value **4.5** which close to **5** (strongly agree).
9. The answers of learners about if the system flexible to interact with them or not. we found that the percentage ranged between value **4** (agree) which is the minimum value with percentage of **66.7 %** and the maximum value **5** (strongly agree) with percentage of **33.3 %** in where the mode and the median of their answers is value **4** (agree).
10. The answers of learners about if integrating adaptive learning path in the system helps them to understand learning concepts or not. we found that the percentage ranged between value **4** (agree) which is the minimum value with percentage of **33.3 %** and the maximum value **5** (strongly agree) with percentage of **66.7 %** in where the mode and the median of their answers is value **5** (strongly agree).

11. The answers of learners about if the adaptation techniques within the course is clear and understandable or not. we found that the percentage ranged between value **4** (agree) which is the minimum value with percentage of **66.7 %** and the maximum value **5** (strongly agree) with percentage of **33.3 %** in where the mode and the median of their answers is value **4** (agree).
12. The answers of learners about if easy to know which part need more study using the provided adaptation techniques or not. We found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **50 %** and the maximum value **5** (strongly agree) with percentage of **50 %** in where there are two modes (four and five) and the median of their answers is value **4.5**, which close to **5** (strongly agree).
13. The answers of learners about if it is useful to navigate through course or not. we found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **66.6 %** and the maximum value **5** (strongly agree) with percentage of **33.3 %** in the modes and the median of their answers is value **4** (agree).
14. The answers of learners about if the Synchronization between ILOs and learning concepts draws learners attention or not. we found that the answers and the percentage ranged between value **3** which is the minimum value with percentage of **33.3 %** and the maximum value **5** with percentage of **33.3 %** in where there are three modes (three, four and five) and the median of their answers is value **4**.
15. The answers of learners about if the provided adaptation techniques are needed for better understanding of a course or not. we found that the answers and the

percentage ranged between value **1** (strongly disagree) which is the minimum value with percentage of **16.7 %** and the maximum value **5** (strongly agree)with percentage of **16.7 %** in where the modes and the median of their answers is value **4** (agree).

16. The answers of learners about if the providing learning concepts part is useful or not. we found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **50 %** and the maximum value **5** (strongly agree) with percentage of **50 %** in where there are two modes (four and five) and the median of their answers is value **4.5** which is close to **5** (strongly agree).
17. The answers of learners about if the providing recommended concepts part is useful or not. we found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **50 %** and the maximum value **5** (strongly agree) with percentage of **50 %** in where there are two modes (four and five) and the median of their answers is value **4.5** which is close to **5** (strongly agree).
18. The answers of learners about if Learner used recommended learning concepts better understanding of a course or not. we found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **50 %** and the maximum value **5** (strongly agree) with percentage of **50 %** in where there are two modes (four and five) and the median of their answers is value **4.5**, which is close to **5** (strongly agree).

19. The answers of learners about if Learner used related learning concepts better understanding of a course or not. we found that the answers and the percentage ranged between value **4** (agree) which is the minimum value with percentage of **66.7 %** and the maximum value **5** (strongly agree) with percentage of **33.3 %** in where modes and the median of their answers is value **4** (agree).
20. The answers of learners about if Learner prefer to follow a classical course without using the adaptive MOOCs or not. we found that the answers and the percentage ranged between value **1** (strongly disagree) which is the minimum value with percentage of **50 %** and the maximum value **4** (agree) with percentage of **16.7** % in where the mode is value **1** (strongly disagree) and the median of their answers is value **1.5** which is close to **2** (disagree).

5.2.4 Workload Perception Questionnaire(WPQ)

Table 12: Workload Perception-Percentage Frequency

#	Workload Perception Questionnaire (WPQ)	Percentage frequency				
		strongly disagree(1)	disagree (2)	Neutral (3)	agree (4)	strongly agree (5)
1	Mental Demand: How mentally demanding was the task?	0.00	50.00	50.00	0.00	0.00
2	Physical Demand: How physically demanding was the task?	16.67	16.67	66.67	0.00	0.00
3	Performance: How successful where you in accomplishing what you were asked to do?	0.00	0.00	16.67	66.67	16.67
4	How hard did you have to work to accomplish your level of performance?	16.67	66.67	16.67	0.00	0.00
5	Frustration: How insecure, discouraged, irritated, stressed and annoyed where you using the Course?	66.67	16.67	16.67	0.00	0.00

Table 13: Workload Perception-Mean and St.dev

#	Workload Perception Questionnaire (WPQ)	Mean	St.dev
1	Mental Demand: How mentally demanding was the task?	2.50	0.55
2	Physical Demand: How physically demanding was the task?	2.50	0.84

3	Performance: How successful where you in accomplishing what you were asked to do?	**4.00**	**0.63**
4	How hard did you have to work to accomplish your level of performance?	**2.00**	**0.63**
5	Frustration: How insecure, discouraged, irritated, stressed and annoyed where you using the Course?	**1.50**	**0.84**

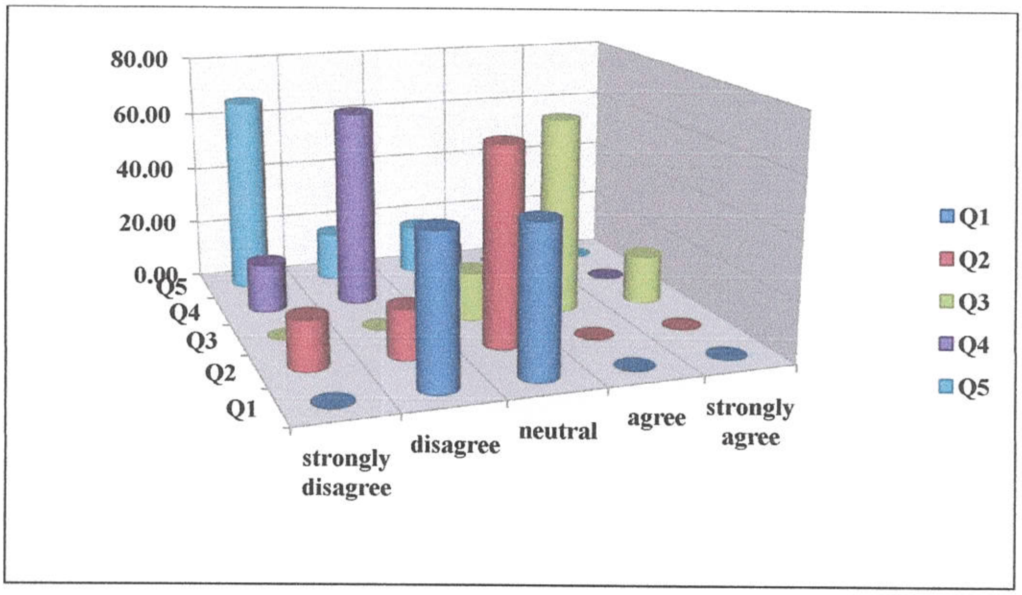

Figure 23: Workload Perception Questionnaire (WPQ)

As we seen in table 12, table 13, and figure 23, we can conclude the following:

1. In Q1 : The answers of the participants range between value **2** (disagree) which is the minimum value with percentage of **50%** and the maximum value **3** (neutral) with percentage of **50%** in which there are two modes (two and three) and the median is equal **1.5** which is close to **2** (disagree).
2. In Q2 : The answers of the participants range between **1** (strongly disagree) which is the minimum value with percentage of **16.7%** and the maximum value **3** (neutral) with percentage of **66.7%** in where the mode and the median of their answers are, the value **3** (neutral).

3. In Q3 : The answers of the participants range between **3** (neutral) which is the minimum value with percentage of **16.7%** and the maximum value **5** (strongly agree) with percentage of **16.7%** in where the mode and the median of their answers are, the value **4** (agree).
4. In Q4 : The answers of the participants range between **1** (strongly disagree) which is the minimum value with percentage of **16.7%** and the maximum value **3** (neutral) with percentage of **16.7%** in where the mode and the median of their answers are, the value **2** (disagree).
5. In Q5 : The answers of the participants range between **1** (strongly disagree) which is the minimum value with percentage of **66.7%** and the maximum value **3** (neutral) with percentage of **16.7%** in where the mode and the median of their answers are, the value **1** (strongly disagree).

5.3 The Third Stage of Experiment Evaluation

At this stage, the system was presented to five educators individually with a highlight of all its functions, its working principle, and the method of its use. Also, the idea of the system was explained which depends on the selection of learners for a set of Intended Learning Outcomes (ILOs) that they would like learning it. After that, we moved inside the system from the learning materials offered to the relevant recommended resources. Then, to the learning path that shows the learning concepts that have been passed and which have not been exceeded, and the learning concepts that rely on previous learning concepts. Also from there, we moved to the electronic assessment, which measures the learner's understanding of the learning materials that was presented.

Several questions were asked to the educators about the system, these questions are:

1. What is their opinion about the idea of the system, which depends on retrieval of the learning materials and recommended resources based on the Intended Learning Outcomes (ILOs) ?
2. To what extent are the offered learning materials relevant to learning concepts?
3. Does is having a learning path and selecting a learning style a good idea for the learner?

From the point of view of educators, the idea of adapting of the ILOs as an option to retrieve learning materials is a good and ideal idea if applied in a real systems. One of the educators mentioned that " This idea is so excellent so that the learning materials are presented based on selected learning outcomes. But it needs more work to become more specific and more advanced". The truth lies in this idea is that it helps learners to reduce their time, effort and money, as well as their access to what they want to learn in more precisely and efficiently.

With regard to the presentation of the recommended resources, the second educator pointed mentioned that it is a good idea to encourage the learner to see other relevant resources, which increases the level of learner knowledge's about specific learning concept.

As to the extent to which the presented learning materials are related to the learning concept, more than one of the learning concepts was selected by the educators. Then, the offered learning materials were examined. It has been shown that this learning materials provides a direct explanation of the learning concept selected.

With regard to the idea of the learning path and the learning style, the educators have been unanimously agreed that it is an effective improvements for learners. The learning path enables learners to learn the path that must be followed to master the ILOs that have been selected. Also, The learner can follow his progress in learning process.

On the other hand, the ability of the learner to select the learning style that he preferred, encourages him to participate in online learning platforms and read the courses that he wants in the preferred style for him.

5.4 Discussion

To end, this system enables learners to follow a course based on his intended learning outcome rather than following a predefined course which is more teacher oriented rather than learner oriented. This system improves the idea of having a course which is learner oriented by delivering learning materials that meet his goals and objectives. Therefore, the system has been evaluated to ensure that this idea has been realized.

So that, the evaluation process has been divided into three main stages. The first stage, the effectiveness of the proposed system was evaluated based on compared the manually matching results between ILOs, learning materials and recommended resources to results have been obtained using the Naive Bayesian Classifier algorithm. To achieve this goal, the precision and recall indicators were used, which showed that the results were promising as the precision-recall indicators provided a good results in the classification process.

The second stage of evaluation focused on the learners' assessment of the proposed system. So that, a descriptive analysis was performed to a set of questionnaires has been filled out by six learners who have experimented the proposed system. This questionnaire was covered four main aspects as follows:

The first aspect of the questionnaire, the Demographic Questionnaire for Learners (DQL): this aspect was presented the demographic characteristics of learners which include age of learners, and the usage of e-learning applications by the learner in which the answers was ranged between less frequently than once a week and several times.

The second aspect is the System Usability Scale Acceptance (SUS) which was presented a questions that are regarding with the usability of the system in real world. As a result of students' answers to these questions, their future use of the proposed adaptive MOOCs system ranged from **4** (agree) to **5** (strongly agree). Besides that, their responses ranged from agree and strongly agree to recommend their colleagues to experience the proposed system.

The third aspect is the Subjective Impression Questionnaire (SIQ). According to learners answers in section 5.2.3, the learners have given a positive impression about the idea of the proposed system in terms of ease to use without need for technical person to help them. Also, it was easy form to become skilful at using the adaptive MOOC course. In addition to Integrating adaptive learning path to understand learning concepts being studied.

And finally, the Workload Perception Questionnaire (WPQ) was presented a questions that are related to mental demand, physical demand, performance and frustration. So that students' responses ranged from **4** (agree) and **5** (strongly agree) to their success in accomplishing what they wanted. As well as with regard to insecure, discouragement, irritated, stressed and annoyed during the use of the proposed system, their answers ranged from **1** (strongly disagree), **2** (disagree) and **3** (neutral). Therefore, this aspect of the system needs more work to be more secure and comfortable.

Beside that, some ideas for the development of the proposed system were collected as a feedback from learners such as adding more recommended resources and providing more descriptions about the learning materials.

In the last stage of the evaluation, the proposed work and its performance was evaluated by five educators in several aspects so that their answers confirmed that the idea of the proposed system is good and ideal. Also, it is an important improvement for educators and learners.

5.5Summery

This chapter provided detailed explanation on the experiments that have been performed to evaluate the proposed system. The evaluation was carried out at three stages. The first stage, the proposed system was evaluated by using the precision and recall indicators in order to estimate the effectiveness when utilizing the Naive Bayesian Classifier technique in matching process between the ILOs and learning materials and in recommending new learning resources. The second stage of the evaluation is a descriptive analysis was conducted to a set of questionnaires has been filled out by six learners who have experimented the proposed system. In the last stage of evaluation, the proposed work was evaluated by five educators in several aspects, such as the added value of the recommendation of new learning resources, the adaptive learning path in order to meet the learning outcomes that he wants to learn.

CHAPTER 6

CONCLUSION AND FUTUREWORK

In this chapter, a conclusion about the proposed system is presented. In addition, the outline of future works that are associated to exploiting other ideas and techniques in order to enhance the performance of the proposed system has been proposed.

This chapter is organized as follows: Section 6.1 presents a summary for this thesis and highlights the framework and the techniques that has been carried out in the proposed system. Section 6.2 provides the future work that are related to employing other ideas and techniques in developing the adaptive MOOCs system.

6.1 Conclusion

Recently, Online adaptive MOOCs is one of the most important platforms of online learning in higher education Institutions. Accordingly, online adaptive MOOCs systems have been proposed to support the learners in any geographical area. And in order to access courses that meet their relevant needs in less time and effort required for learning. Several frameworks and techniques have been offered to build online adaptive MOOCs systems. However, these frameworks and techniques suffer from obstacles and drawbacks.

In this thesis, an adaptive MOOCs framework was presented to improve the learner performance based on Intended Learning Outcomes (ILOs). As a result, the learner explores the learning materials through specific learning path which will be generated adaptively to master the learning outcomes that he wants to acquire. To satisfy that, the proposed framework was depending on a number of principles and conceptual models that have been developed from existing frameworks to support adaptivity in MOOCs.

The proposed framework was innovative in different aspects. First, pedagogical aspects which were considered explicitly by mapping the learning concepts with different pedagogical relationships. Second, adaptivity was realized based on intended learning outcomes so that the learning process can be learner-oriented rather than teacher-oriented. Third, learning style was considered in the delivering process of learning materials for learning concepts.

Furthermore, the development of the proposed system was conducted to provide the learning materials, assessments and recommended resources based on the Intended Learning Outcomes (ILOs) that are selected by the learners. This research work included two main phases that were carried out as follows: the first phase is related to manual mapping between the ILOs and learning materials. The second phase associated with automatic mapping between ILOs and learning materials by using the Naive Bayesian Classifier algorithm.

Therefore, The evaluation of the proposed adaptive MOOCs system based on the ILOs has been carried out at three stages: the first stage evaluated the proposed system by using the Precision and Recall indicators in order to estimate the effectiveness when utilizing the Naive Bayesian Classifier technique in the matching process between the ILOs, learning materials and in recommending new learning resources. The second stage of the evaluation is a descriptive analysis was performed to a set of questionnaires has been filled out by six learners who have experimented the proposed system. In the last stage of evaluation, the proposed work was evaluated by five educators in several aspects, such as the added value of the recommendation of new learning resources, the adaptive learning path in order to meet the learning outcomes that he wants to learn.

Consequently, the results were promising as the precision-recall indicators provided a good results in the classification process. Additionally, the questionnaire provided a good results and a positive impression from the point of view of educators and learners.

6.2 Future work

Though conducted this framework showed promising outcomes, there are other remaining limitation and problems that need to be addressed in the future. we mention several limitations and problems that can be addressed them in the future work.

- In chapter 3, we have illustrated how employing the Naive Bayesian Classifier technique to achieve this research purpose in mapping between the ILOs and learning materials. Then, providing the adaptation of learning materials and recommended resources that are related to selected ILOs for the learner. In this context, because the idea is still new, no research have been applied any other classification techniques to retrieve the learning materials based on the intended learning outcomes (ILOs). Therefore, the implementation of other classification techniques as support vector machine, decision tree have been proposed to compare the results and obtain the best technique in this field. Furthermore, a combination of classification algorithms can be used in the automatic mapping process between ILOs and learning materials of a specific course.

- The need to consider a comprehensive enrichment of ILOs and learning materials that can be considered for a topic.
- The need to conduct additional experiments to validate the effectiveness of the proposed framework as well as to validate the learner satisfaction, attitude and its effect on drop-out rate of MOOCs courses.
- Another idea is related to the granting of a certificate for learners after completing the course based on achieving the minimum number of intended learning outcomes (ILOs).

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Appendix A: Questionnaire of Adaptive MOOC-Algorithms Course Evaluation

Information and consent to participate in evaluation of Adaptive MOOC tools.

You have been asked to participate in the Adaptive MOOC Course Evaluation. This study aims at evaluating the tool called the Adaptive MOOC Course. We would like to get your feedback on the tools, their usability and possible benefits or drawbacks. The outcomes of the evaluation will give evidence of the quality of the Adaptive MOOC Course and will be used to derive ideas on how the system can be further improved. In general, there are no right or wrong answers. We want to know your opinion and viewpoints. The information that is obtained in connection with this study will be kept anonymous in the context of the overall evaluation. In respect for each other, we also ask you to keep responses confidential. It is important to remember that this is not an evaluation of you personally. Rather, we are interested in your personal evaluation of the system that you are working on.

If you have any questions about the study, please feel free to ask.

I understand this information and agree to participate.

There are 43 questions in this survey

A. Demographic Questionnaire for Learners (DQL)

Thank you for participating in this study! First we would like to collect some background data that are relevant to our research work. Please answer the questions below. Your data and the information collected in this evaluation will be treated anonymously.

1. Age..
2. How often do you learn from the internet in general?
   Please choose only one of the following:
   - Never
   - Less frequently than once a week
   - Several times a week
   - Daily
3. How often do you use e-learning applications (including coursera, udemy, edx, etc.)?Please choose only one of the following:
   - Never
   - Less frequently than once a week
   - Several times a week
   - Daily
4. How much time in minutes did you spend approximately on the provided adaptive course? ....

B. Usability - System Usability Scale (SUS)

Please answer the questions below – record your immediate response to each item, rather than thinking about it for a long time. Please respond to all items – if you have the feeling you cannot answer a particular item, check the centre point of the scale.

1=strongly disagree 5=strongly agree

1. I think that I would like to use the adaptive MOOC course.

1		2		3		4		5	

2. I found the Adaptive MOOC course is unnecessarily complex.

1		2		3		4		5	

3. I think the adaptive MOOC is easy to use.

1		2		3		4		5	

4. I think that I would need the support of a technical person to be able to use this Course in the future.

1		2		3		4		5	

5. I found the various parts in this adaptive MOOC course were well integrated.

1		2		3		4		5	

6. I think there is too much inconsistency in this Course.

1		2		3		4		5	

7. I would imagine that most of my classmates would learn to use this Course very quickly.

1		2		3		4		5	

8. I found the adaptive MOOC Course very cumbersome to use.

1		2		3		4		5	

9. I felt very confident using the adaptive MOOC Course.

1		2		3		4		5	

10. I needed to figure out a lot of things before I could get going with this Course.

1		2		3		4		5	

11. I would like to use this adaptive Course in the future.

1		2		3		4		5	

12. I would recommend this adaptive course to my colleagues.

1		2		3		4		5	

C. Acceptance: Subjective Impression Questionnaire (SIQ)

The following sentences describe thoughts and feelings you may have regarding the use of the Adaptive MOOC Course. For each of the following statement please indicate how much you can agree on the given scale.

1=strongly disagree 5=strongly agree

1. I would use the adaptive MOOC Course whenever possible.

1		2		3		4		5	

2. I would use the adaptive MOOC Course frequently when it is available.

1		2		3		4		5	

3. Using the adaptive course is a good idea.

1		2		3		4		5	

4. Using the adaptive Course is unpleasant.

1		2		3		4		5	

5. Using the adaptive MOOC Course would be beneficial to my learning.

1		2		3		4		5	

6. Using the adaptive MOOC Course is easy for me.

1		2		3		4		5	

7. It was easy for me to become skilful at using the adaptive MOOC Course.

1		2		3		4		5	

8. I find the adaptive MOOC Course easy to use.

1		2		3		4		5	

9. I find the adaptive MOOC Course to be flexible to interact with.

1		2		3		4		5	

10. Integrating adaptive learning path helps me to understand learning concepts being studied.

1		2		3		4		5	

11. Provided adaptation techniques within the Course is clear and understandable.

1		2		3		4		5	

12. It is easy to know which part is required for more study using the provided adaptation techniques.

1		2		3		4		5	

13. It is useful to navigate through course

1		2		3		4		5	

14. Synchronization between ILOs and learning concepts draws your attention.

1		2		3		4		5	

15. The provided adaptation techniques are needed for better understanding of a course (e.g. Algorithm course)

1		2		3		4		5	

16. Providing related concepts part is useful

1		2		3		4		5	

17. Providing recommended concepts part is useful

1		2		3		4		5	

18. I used recommended learning concepts better understanding of a course (e.g. Algorithm course)

1		2		3		4		5	

19. I used related learning concepts better understanding of a course (e.g. Algorithm course)

1		2		3		4		5	

20. I prefer to follow a classical course without using the adaptive MOOC.

1		2		3		4		5	

D. Workload Perception Questionnaire (WPQ)

The purpose of this short questionnaire is to measure the perceived workload while learning and working with the Adaptive MOOC system (subsequently referred to as 'task').Please answer the questions below by rating each item based on your subjective impression.

1-Very Low5=Very High

1. Mental Demand: How mentally demanding was the task?

1		2		3		4		5	

2. Physical Demand: How physically demanding was the task?

1		2		3		4		5	

3. Performance: How successful where you in accomplishing what you were asked to do?

1		2		3		4		5	

4. How hard did you have to work to accomplish your level of performance?

1		2		3		4		5	

5. Frustration: How insecure, discouraged, irritated, stressed and annoyed where you using the Course?

1		2		3		4		5	

E. Qualitative feedback: User Feedback Questionnaire – Qualitative Feedback (UFQQ)

1. What did you like best about the system and the Course?

Please write your answer here:

2. What did you like least about the system and Course?

Please write your answer here:

3. What should be improved and how?

Please write your answer here:

Thank you for your participation in this evaluation.

Appendix B: Tables and Figures of Descriptive Analysis Questionnaire of Adaptive MOOC System Evaluation.

B.1 : Demographic Questionnaire for Learners (DQL) :

Table 7 : Learn from the Internet and use learning applications

	Never	Less frequently than once a week	Several times a week	Daily
How often do you learn from the internet in general?	0.00	16.67	83.33	0.00
How often do you use e-learning applications (including coursera, udemy, edx, etc.)?Please choose only one of the following:	0.00	83.33	16.67	0.00

B.2 : Usability - System Usability Scale (SUS) :

Table 8: System Usability Scale (SUS) - Percentage frequency

Usability - System Usability Scale (SUS)		Percentage frequency				
		strongly disagree	disagree	neutral	agree	strongly agree
1	I think that I would like to use the adaptive MOOC course.	0.00	0.00	0.00	83.33	16.67
2	I found the Adaptive MOOC course is unnecessarily complex.	16.67	33.33	16.67	0.00	33.33
3	I think the adaptive MOOC is easy to use.	0.00	0.00	0.00	66.67	33.33
4	I think that I would need the support of a technical person to be able to use this Course in the future.	33.33	50.00	16.67	0.00	0.00
5	I found the various parts in this adaptive MOOC course were well integrated.	0.00	0.00	0.00	83.33	16.67
6	I think there is too much inconsistency in this Course.	16.67	50.00	33.33	0.00	0.00
7	I would imagine that most of my classmates would learn to use this Course very quickly.	0.00	0.00	0.00	83.33	16.67
8	I found the adaptive MOOC Course very cumbersome to use.	50.00	33.33	0.00	16.67	0.00
9	I felt very confident using the adaptive MOOC Course.	0.00	0.00	0.00	66.67	33.33
10	I needed to figure out a lot of things before I could get going with this Course.	33.33	33.33	0.00	0.00	33.33
11	I would like to use this adaptive Course in the future.	0.00	0.00	0.00	66.67	33.33
12	I would recommend this adaptive course to my colleagues.	0.00	0.00	0.00	16.67	83.33

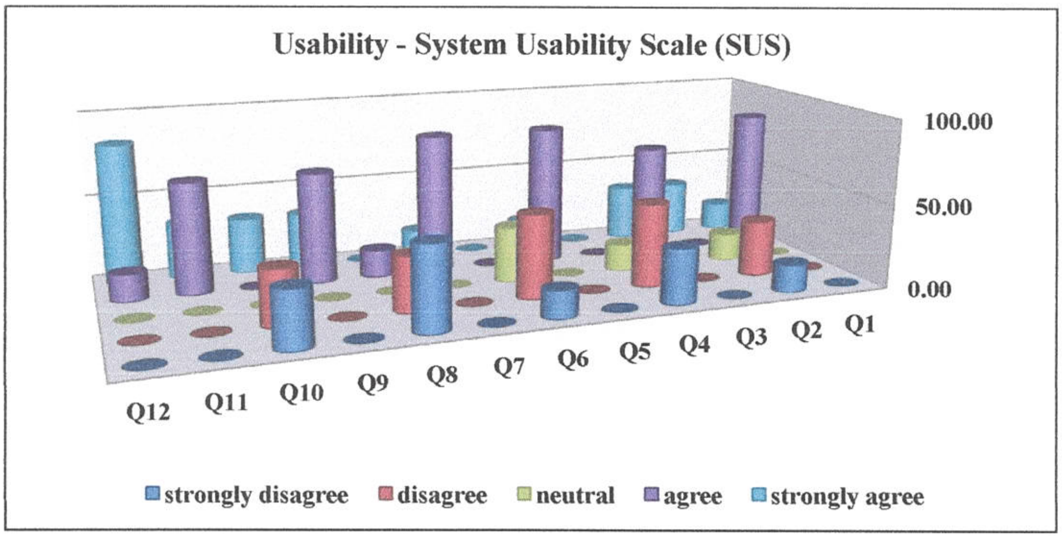

Figure 21: System Usability Scale (SUS) - Percentage frequency

Table 9 : System Usability Scale (SUS) -Mean and St.dev

	Usability - System Usability Scale (SUS)	Mean	St.dev
1	I think that I would like to use the adaptive MOOC course.	4.17	0.41
2	I found the Adaptive MOOC course is unnecessarily complex.	3.00	1.67
3	I think the adaptive MOOC is easy to use.	4.33	0.52
4	I think that I would need the support of a technical person to be able to use this Course in the future.	1.83	0.75
5	I found the various parts in this adaptive MOOC course were well integrated.	4.17	0.41
6	I think there is too much inconsistency in this Course.	2.17	0.75
7	I would imagine that most of my classmates would learn to use this Course very quickly.	4.17	0.41
8	I found the adaptive MOOC Course very cumbersome to use.	1.83	1.17
9	I felt very confident using the adaptive MOOC Course.	4.33	0.52
10	I needed to figure out a lot of things before I could get going with this Course.	2.67	1.86
11	I would like to use this adaptive Course in the future.	4.33	0.52
12	I would recommend this adaptive course to my colleagues.	4.83	0.41

B.3 : Acceptance: Subjective Impression Questionnaire (SIQ) :

Table 10: Subjective Impression Questionnaire (SIQ)- frequency Percentage

#	Acceptance: Subjective Impression Questionnaire (SIQ)	Percentage frequency				
		strongly disagree	disagree	Neutral	agree	strongly agree
1	I would use the adaptive MOOC Course whenever possible.	0.00	0.00	0.00	66.67	33.33
2	I would use the adaptive MOOC Course frequently when it is available.	0.00	0.00	0.00	50.00	50.00
3	Using the adaptive course is a good idea.	0.00	0.00	0.00	0.00	100.00
4	Using the adaptive Course is unpleasant.	50.00	50.00	0.00	0.00	0.00
5	Using the adaptive MOOC Course would be beneficial to my learning.	0.00	0.00	0.00	66.67	33.33
6	Using the adaptive MOOC Course is easy for me.	0.00	0.00	0.00	50.00	50.00
7	It was easy for me to become skilful at using the adaptive MOOC Course.	0.00	0.00	0.00	33.33	66.67
8	I find the adaptive MOOC Course easy to use.	0.00	0.00	0.00	50.00	50.00
9	I find the adaptive MOOC Course to be flexible to interact with.	0.00	0.00	0.00	66.67	33.33
10	Integrating adaptive learning path helps me to understand learning concepts being studied.	0.00	0.00	0.00	33.33	66.67
11	Provided adaptation techniques within the Course is clear and understandable.	0.00	0.00	0.00	66.67	33.33
12	It is easy to know which part is required for more study using the provided adaptation techniques.	0.00	0.00	0.00	50.00	50.00
13	It is useful to navigate through course	0.00	0.00	0.00	66.67	33.33
14	Synchronization between ILOs and learning concepts draws your attention.	0.00	0.00	33.33	33.33	33.33
15	The provided adaptation techniques are needed for better understanding of a course (e.g. Algorithm course)	16.67	0.00	16.67	50.00	16.67
16	Providing related concepts part is useful	0.00	0.00	0.00	50.00	50.00
17	Providing recommended concepts part is useful	0.00	0.00	0.00	50.00	50.00
18	I used recommended learning concepts better understanding of a course (e.g. Algorithm course)	0.00	0.00	0.00	50.00	50.00
19	I used related learning concepts better understanding of a course (e.g. Algorithm course)	0.00	0.00	0.00	66.67	33.33
20	I prefer to follow a classical course without using the adaptive MOOC.	50.00	33.33	0.00	16.67	0.00

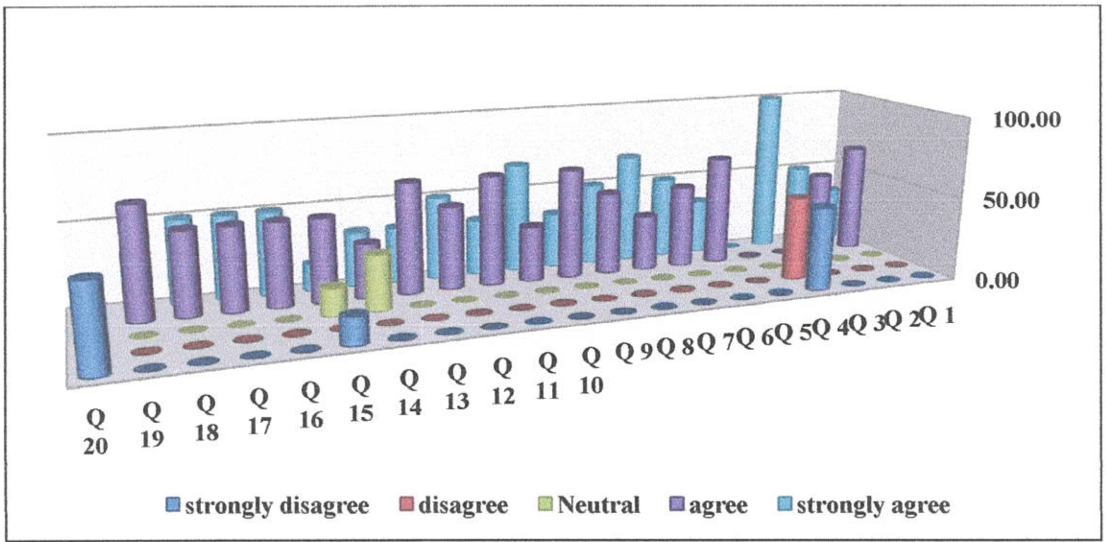

Figure 22 : Subjective Impression Questionnaire (SIQ)

Table 11 : Subjective Impression Questionnaire (SIQ)-Mean and St.dev

#	Acceptance: Subjective Impression Questionnaire (SIQ)	Mean	St.dev
1	I would use the adaptive MOOC Course whenever possible.	4.33	0.52
2	I would use the adaptive MOOC Course frequently when it is available.	4.50	0.55
3	Using the adaptive course is a good idea.	5.00	0.00
4	Using the adaptive Course is unpleasant.	1.50	0.55
5	Using the adaptive MOOC Course would be beneficial to my learning.	4.33	0.52
6	Using the adaptive MOOC Course is easy for me.	4.50	0.55
7	It was easy for me to become skilful at using the adaptive MOOC Course.	4.67	0.52
8	I find the adaptive MOOC Course easy to use.	4.50	0.55
9	I find the adaptive MOOC Course to be flexible to interact with.	4.33	0.52
10	Integrating adaptive learning path helps me to understand learning concepts being studied.	4.67	0.52
11	Provided adaptation techniques within the Course is clear and understandable.	4.33	0.52
12	It is easy to know which part is required for more study using the provided adaptation techniques.	4.50	0.55
13	It is useful to navigate through course	4.33	0.52
14	Synchronization between ILOs and learning concepts draws your attention.	4.00	0.89
15	The provided adaptation techniques are needed for better understanding of a course (e.g. Algorithm course)	3.50	1.38
16	Providing related concepts part is useful	4.50	0.55
17	Providing recommended concepts part is useful	4.50	0.55
18	I used recommended learning concepts better understanding of a course (e.g. Algorithm course)	4.50	0.55

19	I used related learning concepts better understanding of a course (e.g. Algorithm course)	4.33	0.52
20	I prefer to follow a classical course without using the adaptive MOOC.	1.83	1.17

B.4 : Workload Perception Questionnaire(WPQ) :

Table 12:Workload Perception-Percentage Frequency

#	Workload Perception Questionnaire (WPQ)	Percentage frequency				
		strongly disagree	disagree	neutral	agree	strongl y agree
1	Mental Demand: How mentally demanding was the task?	0.00	50.00	50.00	0.00	0.00
2	Physical Demand: How physically demanding was the task?	16.67	16.67	66.67	0.00	0.00
3	Performance: How successful where you in accomplishing what you were asked to do?	0.00	0.00	16.67	66.67	16.67
4	How hard did you have to work to accomplish your level of performance?	16.67	66.67	16.67	0.00	0.00
5	Frustration: How insecure, discouraged, irritated, stressed and annoyed where you using the Course?	66.67	16.67	16.67	0.00	0.00

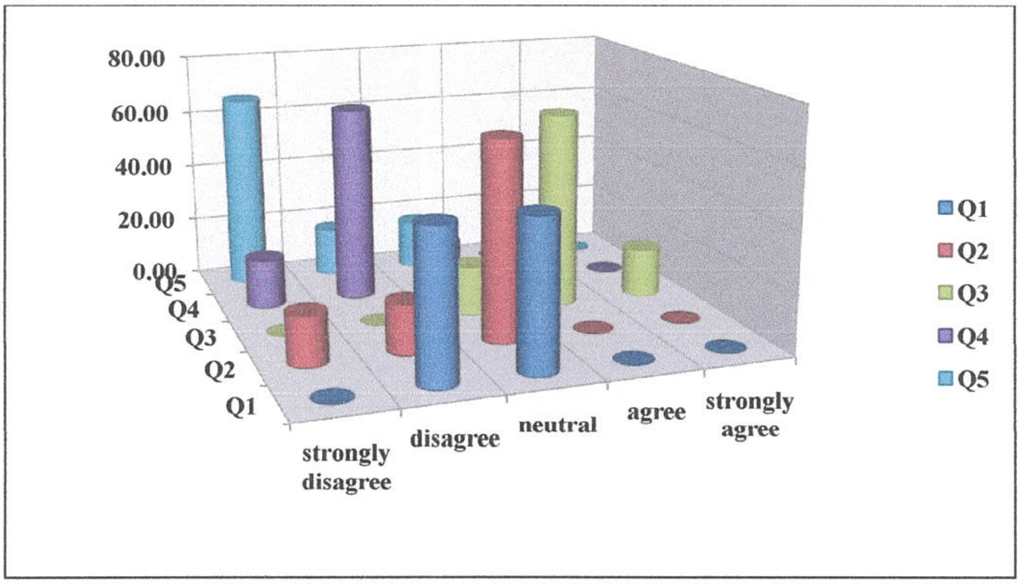

Figure 23 : Workload Perception Questionnaire (WPQ)

Table 13: Workload Perception-Mean and St.dev

#	Workload Perception Questionnaire (WPQ)	Mean	St.dev
1	Mental Demand: How mentally demanding was the task?	**2.50**	**0.55**
2	Physical Demand: How physically demanding was the task?	**2.50**	**0.84**
3	Performance: How successful where you in accomplishing what you were asked to do?	**4.00**	**0.63**
4	How hard did you have to work to accomplish your level of performance?	**2.00**	**0.63**
5	Frustration: How insecure, discouraged, irritated, stressed and annoyed where you using the Course?	**1.50**	**0.84**

الملخص باللغة العربية

نظرا للتطور المتزايد في المجال التعليمي، فإن جميع الاتجاهات الحديثة تتجه نحو بيئات التعلم المفتوحة (المواد التعليمية الهائلة المتاحة عبر الانترنت) التي تقدم العديد من المواد التعليمية في مجالات مختلفة من قبل عدد من أفضل الجامعات في جميع أنحاء العالم. وبالتالي، يمكن للمتعلمين ذوي الخلفيات والخبرات المختلفة تصفح ومتابعة مواد تعليمية مختلفة عبر الانترنت. على الرغم من أن النظم المقترحة لدعم وتكييف المواد التعليمية تمتلك العديد من المزايا التي تتفوق بها على أنظمة التعلم عبر الإنترنت التقليدية، فإنها لا تزال تعاني من العديد من العقبات. من ناحية أخرى، إثراء المواد التعليمية يمكن أيضا أن يكون نقطة ضعف. على سبيل المثال، إتاحة الفرصة لجميع المتعلمين ليتمكنوا من استكشاف عدد كبير من المواد التعليمية في نفس الوقت قد يسبب العديد من المشاكل التي لن تمكن المتعلمين من الحصول على الفوائد والأهداف المطلوبة. وذلك إما لأن مستوى المواد التعليمية ليس مناسبا للمتعلمين أو أن محتويات هذه المواد لا تتطابق مع نتائج التعلم المطلوبة من قبل المتعلم. وهذا يعتبر حافزا في المناقشات الأكاديمية حول مجال التعلم الإلكتروني لدعم المتعلمين عن طريق تكييف العدد الكبير من المواد التعليمية المتاحة عبر الانترنت بما يتناسب مع أهداف المتعلم. بناء على ذلك, تهدف هذه الأطروحة إلى دعم المتعلمين في بيئات التعلم المتاحة عبر الانترنت من خلال القدرة على توفير مواد وموارد تعليمية مناسبة وترتيبها بطريقة تتناسب مع معلومات تتعلق بالمتعلم نفسه كمستوى المعرفة ونتائج التعلم المطلوبة مثلا. وعلى وجه الخصوص، يتطرق هذا العمل إلى المبادئ و المتطلبات والنماذج المستخدمة لتكييف المواد التعليمية استنادا إلى نتائج التعلم المطلوبة التي يحددها المتعلم نفسه. بالإضافة إلى ذلك، يقترح هذا البحث إطارا عاما لتنفيذ عملية التكيف بطريقة تلقائية عن طريق استخدام تقنيات التصنيف.

وقد تم بناء الإطار المقترح واختباره باستخدام مجموعة من المواد والموارد التعليمية التي تم جمعها ونشرها من قبل موقع كورسيرا الالكتروني. وعلاوة على ذلك، تم التحقق من فعالية التقنية المستخدمة في التصنيف وتمت مقارنة النتائج التي تم الحصول عليها مع نتائج تم بناؤها يدويا. وبعد ذلك، أجري تقييم تجريبي لقياس مدى رضا المتعلمين والمعلمين عن الفكرة المقترحة وعن المواد والموارد التعليمية المقدمة لهم من قبل الإطار المقترح في هذه الأطروحة ومدى صلتها بنتائج التعلم المطلوبة . وكانت النتائج واعدة حيث أن مؤشرات القياس قدمت نتائج جيدة في عملية التصنيف. بالإضافة إلى ذلك، قدم الاستبيان نتائج جيدة وانطباعا إيجابيا من وجهة نظر المعلمين والمتعلمين.