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AI Planning System for Adaptive E-Learning

by

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Abstract

Adaptive learning is a way to address the unique needs of an individuals by delivering customized learning content, including resources, exercises, and quizzes. Recent figures indicate that adaptive e-learning systems are considered as one of the most interesting and promising research areas in e-learning education.

The objective of this thesis is to illustrate the current problem statements in e-learning through a comprehensive analysis of literature and existing tools. Additionally it aims to introduce an AI Planning System for adaptive e-learning that effectively addresses these challenges. This report provides a detailed introduction of scope and requirements of the project, the approach and tools employed in its implementation, an objective evaluation from both the developer and user perspectives, and identifies existing deficiencies that require resolution in future work.

In conclusion, the developed AI planning system for adaptive e-learning effectively proves its viability as a valuable learning tool. It is a promising research area and deserves more attention in the future development.

Acknowledgements

I would like to express my sincere appreciation to my supervisor, Prof. Claude Sammut, and my assessor, A/Prof. Nadine Marcus, for providing me with the opportunity to engage in this project. Without their invaluable guidance, support, and expertise throughout my research, I could not have successfully completed this thesis.

Additionally, I want to extend my gratitude to my partner, William Watson, who has also been actively involved in the same project. His efforts in building an impressive website that integrates the Fast-Forward planner with the existing e-learning platform, resulting in the generation of a desirable learning path, deserve fully recognition.

Abbreviations

AI Artificial Intelligence

LMS Learning Management System

LO Learning Object

PDDL Planning Domain Definition Language

FF Fast Forward

ADRIFT Adaptive Dynamic Range Shift

ALCMRS Adaptive Learning Cognitive Map Based System

ALOSI Adaptive Learning Open-Source Initiative

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Under a rapidly developing environment, we are facing that new AI technologies are being invented and scaled at an unexpected rate. However, only a limited number of these advanced technologies have been effectively integrated into education field, which leaves numerous unexploited potentials [1]. The approach of conventional education mainly relies on one-to-many lecturing or tutoring, which fails to sufficiently satisfy the diversity in terms of learning styles, strategies, and preferences of learners [10].

In the past few decades, many researchers pay their attention to education area, making learning become one of the most popular research area. In a technology-driven society, it is widely acknowledged that e-learning could be an effective means of overcoming the constraints of availability, time and spatial restrictions that traditional learning activities impose [11, 23]. However, there are some challenges that have not been addressed by the existing e-learning technologies, in particular the issue of "one size fits all". As reported by [16], the ideal learning strategy encompasses not only providing universal access to resources anytime and anywhere, but also delivering learning activities in the appropriate place, time and manner. Consequently, adaptive e-learning has been recognized as a new trend that could provide more flexible and personalized learning contents rather than a traditional "one size fits all" methodology [6].

This thesis will firstly introduce the common problems encountered in traditional e-learning platforms. Subsequently, several popular adaptive algorithms targeting to mitigate these problems will be discussed. Chapter 2 will provide essential background information on e-learning and AI planning algorithms from literature review. In Chapter 3, we will propose a viable approach for developing an adaptive learning platform and describe the implementation process, followed by an evaluation of the developed platform. Finally, the last chapter will conclude the findings presented in this thesis project and provide recommendations for future research.

1.1 Problem Description

1.1.1 Misalignment between learning resources and learners

Benefiting from the prosperity of the Internet, people have obtained the ability to create various learning content anytime and anywhere. This accessibility, therefore, has resulted in an increase of diversified teaching videos and texts, which reduces the cost of learning and offers people more flexibility to choose their desired learning outcomes. However, needs vary from person to person, which means it is nearly impossible that one learning material can fit the requirements of all learners. Learners, in the meantime, have to spend numerous time in searching the most suitable content among thousands of materials.

For example, if one learner plans to study the "Machine Learning" course on Coursera, there might be more than ten different courses named "Machine Learning", making it struggling to determine which one aligns best with the specific learner's objective. It is hard to know which one is the most matched for that specific user except trying all of those options.

1.1.2 Difficulty in designing an suitable learning plan

In addition to the challenge of learning content mismatch, determining the best-fitted learning path for a specific learner is another headache. For example, one may have such questions:

- How can I identify my weaknesses before the final examination?
- Which learning resources are best fitted to address my specific weaknesses?
- What prior knowledge is required to effectively learn a concept like "A* Algorithm"?

Therefore, the existing challenge is not lack of resources, instead, lack of a mechanism that can efficiently generate a learning plan by selecting appropriate learning materials from a considerable material pool. In some cases, learners themselves are not preciously aware of what they need, which makes the generation of personalized learning paths and content prove to be meaningful and helpful.

1.1.3 Lack of genuine adaptivity on current learning platform

There are a few adaptive learning platforms on the market, such as Smart Sparrow, Knewton, and DreamBox. However, the rationale behind those systems is based on a predefined sequence of learning paths. Once a new user arrives, the system categorizes them using prior test results and recommends learning material according to the predetermined learning path. That means two users will be assigned to the same learning track once they are considered at the same label by the system. However, even if two learners possess the same background, their learning speeds may differ and they do not have to follow the same learning plan. In this way, these existing adaptive learning platforms are regarded as lacking genuine adaptivity.

1.2 Research Questions

The followings are a series of valuable research questions that will be discussed in this thesis:

- Is it possible to make use of existing e-learning platforms that could support creation of interactive learning content?
- What AI planning algorithm or Machine learning algorithm can be used to implement adaptive recommendation?
- Is it possible to build our own adaptive algorithm that can generate appropriate learning routes for students based on the existing e-learning platform?
- How can we break a completed course down to learning objects which is the smallest learning unit for student?
- How can we measure the performance of our designed system?
- What features could be implemented in the future in order to provide better usability of the system?

1.3 Aims and Outcomes

There are a number of goals we want to achieve in this thesis:

- Identify a reusable e-learning platform that could provide basic learning features such as interactive content generation and display.
- Build our own adaptive algorithm on the existing e-learning platform that could display correct learning plan and resources.
- Choose one topic from COMP3411 course, and break it down to several learning objects.
- For each learning object, prepare the corresponding learning materials, including slides and quizzes.
- Translate the learning objects into PDDL and execute on the existing Fast-Forward planner to generate personalized learning path.

- Measure the performance of each learning object by designing reasonable metrics and recording critical data during learning process.
- Evaluate the effectiveness of the current system by user testing.

1.4 Novel Contributions

This thesis project presents the following contributions:

- Creation of learning objects related to the topic of propositional logic, including precondition design, slides write up, and exercises preparation.
- Refinement on the existing web application developed by William Watson, in terms of quizzes system, learning path generation and display.
- Completion of simple user testing by inviting people from different backgrounds and engaging in the learning.

Chapter 2

Background

Research in adaptive systems can be traced back to the early 1990s [5]. With about three decades of development, researchers have been actively exploring ways to integrate adaptivity into e-learning systems. This chapter aims to provide an overview of the current state of art in adaptive learning. It will commence by presenting a series of adaptive algorithms and systems that have been populated in the field. After that, this chapter will discuss the prior contributions made by William Watson.

2.1 Current State of Arts

According to [12], adaptive e-learning is defined as "Adapt the learning's traditional approach in order to satisfy the learner's need and personalized learning." Furthermore, the adaptivity can be categorized to the following two ways [12]:

1. Adaptive presentation support: It decides which content should be delivered to the learner and checks if there is any prerequisite knowledge needed to insert and if any unnecessary information can be hidden. Finally, the information fragments are sorted by their relevance.

2. Adaptive navigation support: It decides how the content will be delivered. There

is a specific group of technologies that support user navigation in hyperspace by adapting to the goals, preferences, and knowledge of the individual user [2].

The implementation of adaptivity is based on a learning system. In the past 5 to 10 years, e-learning systems have gained significant popularity among schools and universities. It gives the ability to real-time upgrading, storing, retrieving, distributing, and sharing information via user's device like PC and mobile phone without adaptability [2]. These popular e-learning systems include Atutor, Blackboard, Moodle, Bodington, BSCW, CLIX, Dokeos, WebCT. The concept of adaptivity was initially introduced in the 1950s, while its prevalence in contemporary times can be attributed to the widespread application of e-learning systems. Therefore the adaptivity is closely linked to e-learning but has the goals in more depth, aiming to deliver learning content tailored to learner's expectations, learning styles, and individual needs. There are many well-known commercial adaptive e-learning system on the market, such as DreamBox, Knewton, ALEKS, and Smart Sparrow.

Figure 2.1 depicts the five components that are included in an adaptive system:

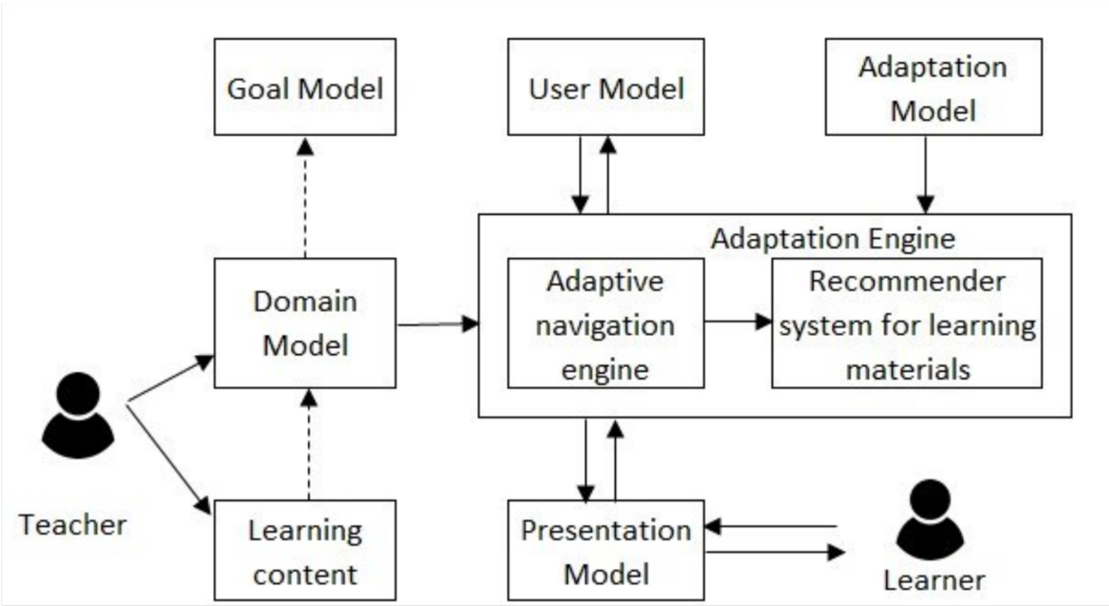

Figure 2.1: Adaptive System Model [2]

- Adaptation Engine: It contains two components - an adaptive navigation engine and a recommendation system. These two components work together to determine the appropriate content to be delivered to learners and the manner in which it is presented.
- User Model: It stores learner profiles, including learning habits, styles, and preferences.
- Domain Model: It stores all learning content, such as teaching videos and exercises.
- Adaptation Model: It encapsulates the adaptive algorithm, which might be AI path planning or machine learning techniques, and the model determines how adaptive the system will be.
- Presentation Model: It is a user interface and responsible for interacting with learners.

From a comprehensive viewpoint, the adaptation engine serves as the core component of the system. It constantly reads and updates user-related data through the user model, selects an suitable adaptation model, and extracts the most appropriate materials from the domain model. Ultimately, the engine seamlessly these materials to the frontend application which correctly renders those contents to learners.

2.2 Learning style model

In recent research, some people hold the view that the learning style potentially influences the recommendation of learning materials. To be more specific, the learning style can be classified into four distinct types: visual, auditory, reading/writing, and kinesthetic [15]. The subsequent enumeration highlights some popular learning style models:

- Learning Style Inventory (LSI) by Kolb: LSI illustrates the state of learning and how people deal with ideas and daily situations. People might have different ways to learn. This inventory can be considered a stimulus for people to interpret and reflect on how they prefer to learn in specific settings. Learning can be regarded as a cycle made up of four basic processes. The LSI takes people through those processes to give a better understanding of how they learn [17].

- Learning Style Questionnaire (LSQ): This questionnaire aims to discover one's preferred learning styles. During the period of growing up people have likely built learning habits that "promote" them benefit more from some experiences than from others. Since they are probably unconscious about it, this questionnaire is intended to pinpoint one's learning preferences so that he or she is able to better select learning materials that suit themselves [14].

- Myers-Briggs Type Indicator: MBTI is an introspective self-report questionnaire that explains different psychological preferences in the world perceiving and decision making of people. The questionnaire tries to categorize participants in four different ways: introversion or extroversion, sensing or intuition, thinking or feeling, judging or perceiving [19].

- Dunn and Dunn Learning Style Questionnaire: By making use of a comprehensive learning style model, the inventory examines how environmental, emotional, sociological, physiological, and psychological preferences affect learning. Dunn and Dunn is considered as one of the most popular Learning Styles Inventories for people to concentrate on their child's learning preferences [18].

Nevertheless, it is important to note that whether the learning style is an effective signal or not in adaptive learning is still a controversial topic. There is no sufficient evidence to show a conclusive relationship between adaptivity and the learning style model in the research.

2.3 Existing adaptive learning algorithms and systems

As indicated in Chapter 1.1.3, the existing adaptive e-learning systems on the market are often deemed inadequate in terms of their adaptivity. Therefore, this chapter aims to introduce a selection of genuinely adaptive learning algorithms or systems.

2.3.1 Adaptive dynamic range shift (ADRIFT) algorithm

ADRIFT is an adaptive learning technique specifically designed for long-history stream-based recommender systems. The algorithm consists of two essential components: the utilization of traditional matrix factoring algorithms commonly used in recommendation systems, such as BRISMF; and the instantaneous update of model based on the results obtained from previous evaluation [7]. In the ADRIFT algorithm, a personalized learning rate, denoted as η_p, is generated and continuously updated for each user ρ (as shown in Figure 2.2 below)[7]. Therefore, the ADRIFT enables dynamic adjustment and enhances the algorithm's ability to adapt to concept drift more effectively. As the concept movements stabilize, the learning rate gradually decreases, thus avoiding unnecessary changes in the learning process and reducing the occurrence of inflated error rates.

Then, we examine the pseudocode presented in Figure 2.3. The output of the ADRIFT algorithm is the learning rate η_p , and its updated value in each iteration is dependent on its previous value and variable s. The variable s is calculated based on the μ_S, which represents short-term changes in a user profile, and the μ_L which refers to long-term changes in a user profile. In a conventional recommendation system, hyperparameters like η_p are predefined and remain unchanged changed throughout the training process. Nevertheless, in the context of ADRIFT, the hyperparameter η_p can learn from historical data, enabling it to adapt and adjust its value based on past observations.

The most significant advantage of the ADRIFT algorithm is its adaptivity. Unlike traditional adaptive algorithms, ADRIFT can effectively react to ongoing changes in user behavior and preferences. Consequently, learners with a faster learning pace will

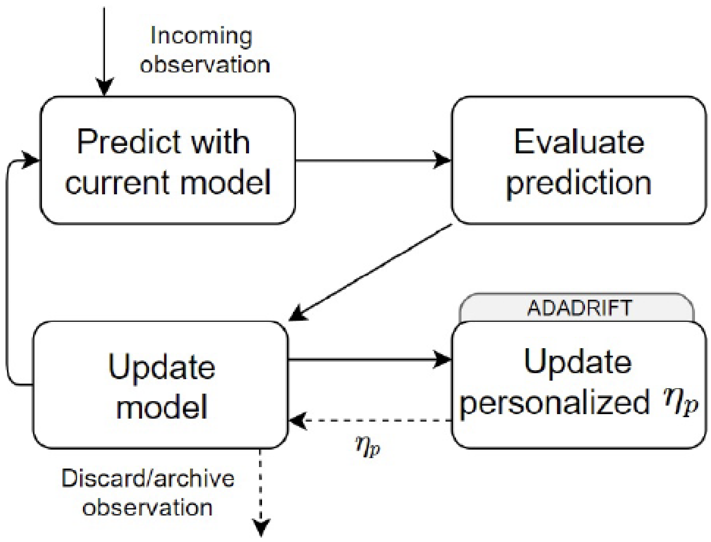

Figure 2.2: The basic working model of ADRIFT [7].

receive recommendations for more advanced and challenging learning materials, while those with a slower learning pace will be provided with relatively easier content and additional exercises. As a result, even though two begin at the same starting point, they can progress at their own individual pace, ensuring a personalized learning experience tailored to their needs and abilities.

2.3.2 Adaptive learning cognitive map based system (ALCMRS)

The Adaptive Learning Cognitive Map-Based System (ALCMRS) is a system that serves the purpose of representing and visualizing a learner's knowledge structure and cognitive state [21]. Similar to ADRIFT, it allows learning contents, learning activities, learning paths, and learning peers to be adjusted continuously, thus providing learners with appropriate learning resources. Figure 2.4 illustrates how learning paths and activities can be visualized by the system. The following are basic concepts used in Figure 2.4 model [21]:

- Subject knowledge (SK): The smallest unit in the SK system in the field.

Algorithm 1: ADADRIFT

/* **Input:** $(err_{ui}B_i - \lambda A_u)$ and p */

/* **Output:** η_p */

/* **Variables:** δ_L, δ_S, α and arrays μ_L, μ_S, η, σ_L n_L, n_S */

/* **Initialization:** Arrays with size $|A|+|B|$. η is an array and each position is initialized to the default value of the matrix factorization technique. Variables μ_L, σ and μ_S do not require initialization values, and n is initialized to 1 for each profile. */

$x \leftarrow (err_{ui}B_i - \lambda A_u)$

$\mu_{L_p} \leftarrow (\mu_{L_p} * (n_{L_p} - 1) + x_\sigma)/n_{L_p}$

$\mu_{S_p} \leftarrow (\mu_{S_p} * (n_{S_p} - 1) + x_\sigma)/n_{S_p}$

$\sigma_{L_p} \leftarrow \left(\sigma_{L_p} * (n_{L_p} - 1) + (x_\sigma - \mu_{L_p})^2\right)/n_{L_p}$

$s \leftarrow (\mu_{S_p} - \mu_{L_p})/\sigma_{L_p}$

$\eta_p \leftarrow \eta_p * \alpha^s$

if $n_{L_p} < \delta_L$ **then**

  $n_{L_p} \leftarrow n_{L_p} + 1$

if $n_{S_p} < \delta_S$ **then**

  $n_{S_p} \leftarrow n_{S_p} + 1$

return η_p

Figure 2.3: The detailed algorithm of ADRIFT [7].

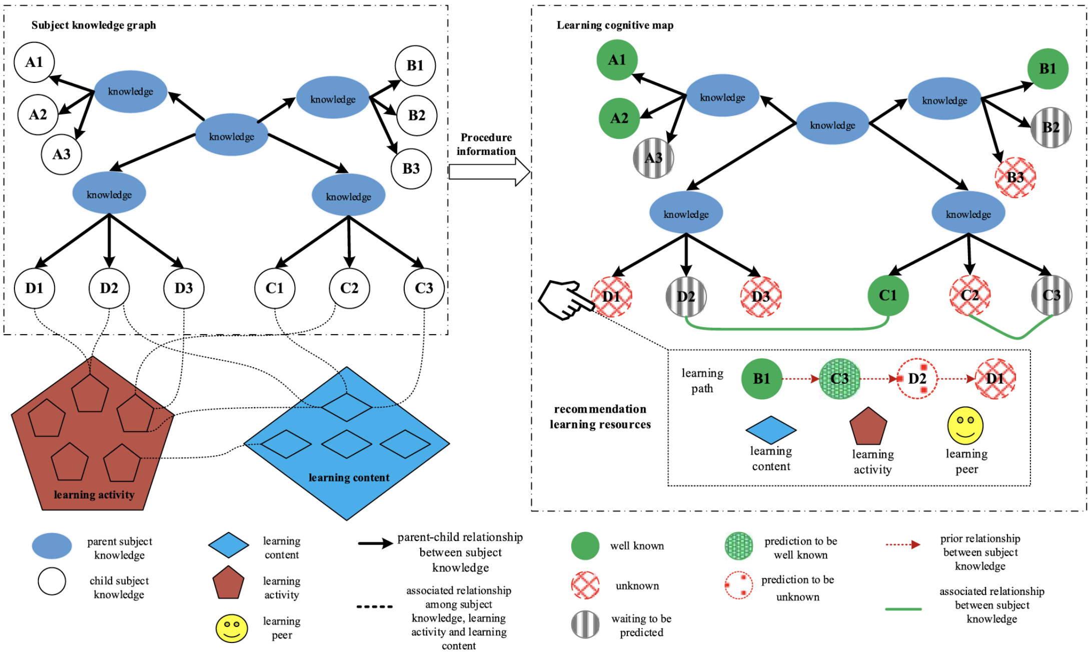

Figure 2.4: The adaptive learning cognitive map model [21].

- Subject knowledge Graph (SK Graph): A graph contains several parent subject knowledge and child subject knowledge as well as the relationship between them.
- Cognitive state: Learner's mastery degree of the SK or concept, ranging from well-known to unknown.
- Learning content: Materials used in the e-learning system which is usually without or only little basic annotation information.
- Learning Activity: It represents the a sequence of actions performed by learners and their associated learning groups, such as learning partners and teachers, to achieve specific learning objectives.
- Learning peer: It refers to learners taking the same course and having the same objectives and requirement to complete the same task.
- Knowledge structure: A graph is used to represent different SK the learner has learnt. It could also display learners' understanding state of the correlation between SK and concept.

- Learning path: It refers to the sequence of prior SK generated to grasp the target SK which initially are labeled as an unknown state.

Figure 2.5 gives the overview of how the system works. To conclude, the whole work flow of ALCMRS is as follows:

1. Firstly, the course teacher produces the learning content, learning activity, and evaluation scheme and annotates subject knowledge through a resource creation module.
2. Secondly, the learner engages in learning through the user interaction module.
3. Thirdly, the system collects and stores learner's behaviour data which is utilized to calculate learners' cognitive state and knowledge structure.
4. Then, the dynamic recommendation module generates recommendations by computing similarities based on the learner's cognitive state, knowledge structure, and annotation information.
5. Finally, the visualization module presents the learner with the knowledge graph and cognitive state, providing a visual representation of their learning progress and understanding.

In detailed, the recommendation module relies on the calculated similarity of the cognitive learning map among different learners. It chooses the learner who has the highest similarity to the current user. The selected learner's learning content, learning activities, learning activities, and learning path are taken into account when making recommendations. With real-time changes of learning progress, the system dynamically updates the most similar peer and adjusts the learning materials accordingly.

2.3.3 ALOSI adaptivity ecosystem

The Adaptive Learning Open-Source Initiative (ALOSI) is an open-source adaptive ecosystem designed to facilitate personalized learning and assessment path planning

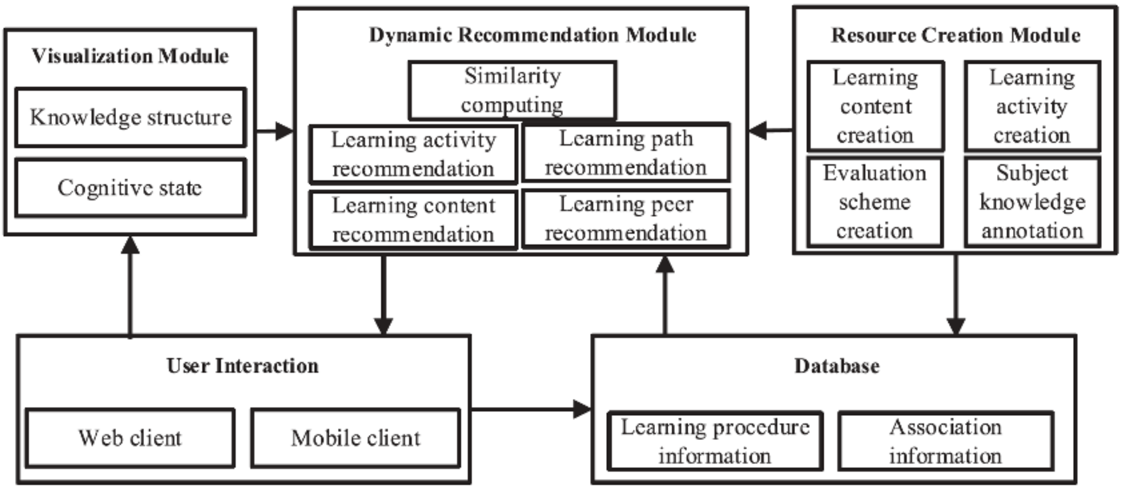

Figure 2.5: The adaptive learning cognitive map model [22].

[20]. Notably, the existing popular learning management systems, including Moodle and Canvas, can be seamlessly integrated into the architecture of ALOSI. A rough framework is given in Figure 2.6. While there are some similarities between the ALOSI system and the previously discussed system, it is important to highlight the key components of ALOSI. The system consists of the frontend learning management system (LMS), the backend content source, the adaptive engine, and the bridging component. In the ALOSI model, the system will still learn from the learner's history and make informed decisions regarding the type of content that should be provided to the learner. This adaptive engine plays a crucial role in tailoring the learning experience to meet the specific needs and preferences of each individual learner.

2.4 AI Planning and PDDL

AI planning is a sub-field within Artificial Intelligence which aims to solve planning and scheduling problems by the exploration of autonomous techniques. According to [13], an AI planning system is tasked with generating a plan that could be one possible solution to a given problem. The following briefly summarise the rationale behind the AI planning system:

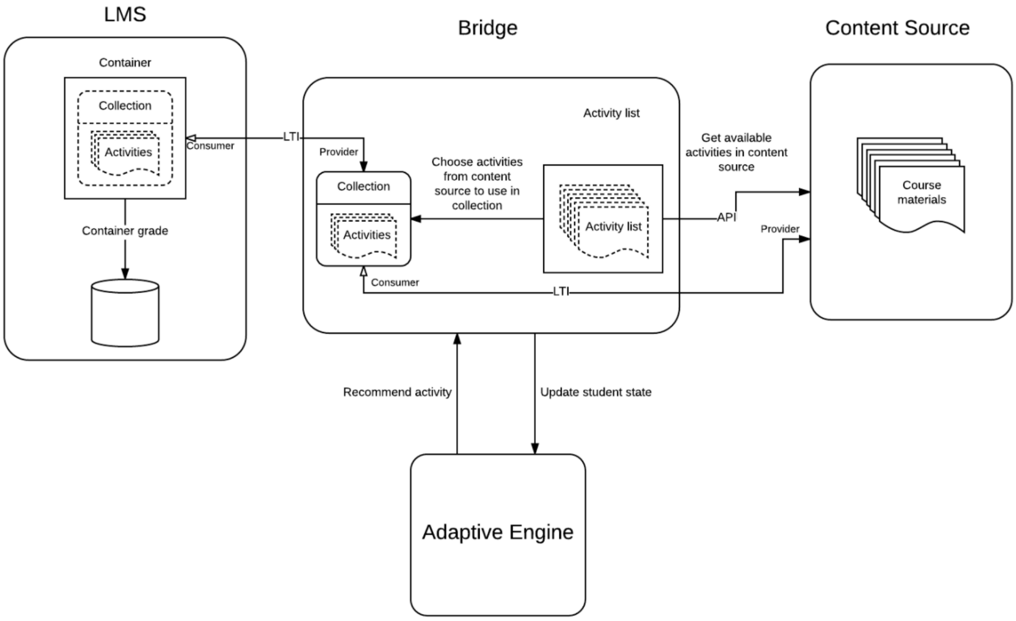

Figure 2.6: The framework of ALOSI [20].

1. A description of the possible initial states of the world, the targeted goals, and a series of possible actions are required to specify before planning.
2. Then, we feed these information into the AI planning system, allowing it to construct a solution which starts from initial states, ends with targeted goals, and satisfies all preconditions of each action.

To some extent, planning can be treated as a searching problem. The planner has to traverse all potential paths in the search space, and finally find a satisfiable path. However, when it comes to a huge problem with many states and actions, the complexity of searching exponentially increase because the search space can be quite large where many interactions happen between different states or partial plans [13].

2.4.1 PDDL

The history of Planning Domain Definition Language (PDDL) can be traced back to the late 1960's. PDDL was based on STRIPS which is used to describe actions and effects of each action, and firstly introduced by Drew McDermott and his colleagues for the 1998 International Conference on Autonomous Planning and Scheduling's AIPS competition [8]. The creation of PDDL is intended to define a formal language that can be used to describe information required in AI planning system. Since its first creation, it has experienced several evolutions, including PDDL2.1, PDDL2.2, PDDL3.0 and PDDL+.

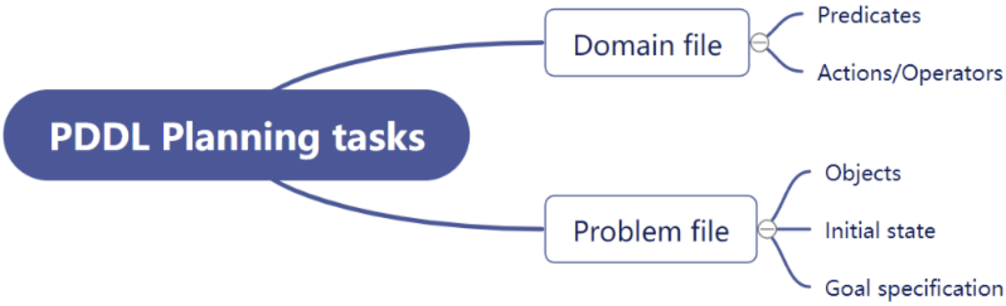

Figure 2.7: The structure of PDDL planning tasks [9].

As shown in figure 2.7, there are 5 components of a PDDL planning task:

1. Objects: Things in the world that interest us.
2. Predicates: Properties of objects that we are interested in, which can be true or false.
3. Initial state: The state we start with in the world.
4. Goal state: The final state we arrive in the world (What things need to be true at completion).
5. Actions/Operators: Multiple ways of changing the state of the world.

In figure 2.8, the implicit formalism behind PDDL is based on two separated models - domain file and problem model. The domain model defines predicates and actions and the problem model specifies objects, initial states and targeted goals. These two models are feed into a PDDL compliant planner and it returns a plan, as a set of ordered actions, which represents an optimal or sub-optimal path to transition from our initial states to our final goals [4].

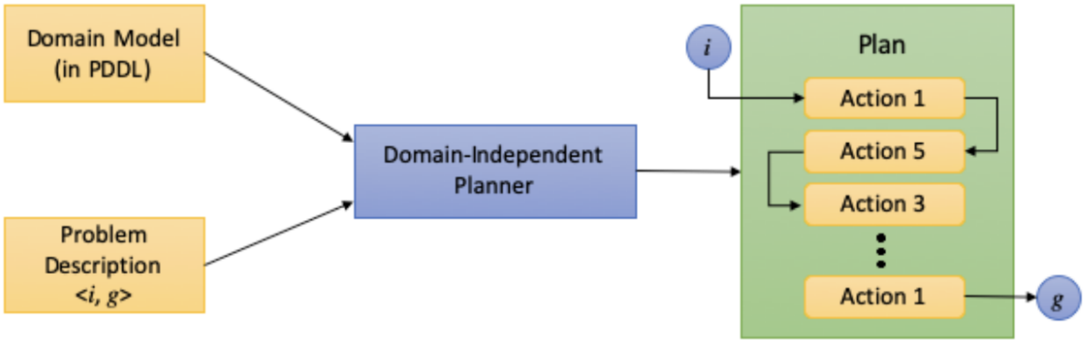

Figure 2.8: Automated Planning System [9].

2.5 Existing E-learning Platforms and AI Planning Tools

We also explore a few e-learning related platforms and tools, and here we mainly focus H5P and Moodle.

- Moodle: It is one of the most famous and popular open-source Learning Management System. Moodle has been adopted by many universities around the world, including UNSW.
- HTML 5 Package (H5P): It is an free and open-source tool that enables users to create, share, and reuse interactive HTML5 content and learning activities, such as interactive videos/audios, slides, exercises, and games. The most advantage of H5P is that it provides a wide range of content types and interactive elements that can be easily embedded into most learning management systems.
- Open eLearning: It is an open-source desktop software where users can easily create, modify and reuse interactive content and learning activities, such as interactive slides and exercises. However, its development team seems to stop updating the software.
- Fast Forward (FF) Planner: The Fast-Forward planner is a domain independent planning system implemented in C language and can handle several planning tasks which are specified in PDDL. The FF is a forward chaining heuristic state

space planner. However, the FF planner does not support full compilation on MacOS and most versions of Windows. After many trials, the FF planner can compile and execute stably on Ubuntu System.

2.6 Previous Work

My another thesis partner - William Watson, built a simple but comprehensive web application. The web application is based on MERN stack, where MERN refers to MongoDB, Express, React and Node. Notably, the web application incorporated e-learning features with the FF planner, enabling dynamic generation of learning routes. To provide an overview of its functionalities, the web application offers the following key features:

- Both teachers and students have the ability to create an account and log in.
- Teachers can create courses, consisting of multiple lessons (referred to as learning objects in the later context). Students can enroll in a published course and access learning content of each lesson under the course.
- Students are able to see a learning routes by triggering frontend button which calls FF planner to generate a learning path based on the specific problem file and domain file.

Chapter 3

Solution and Implementation

3.1 Initial goal and solution

Our initial objective of this thesis is to design and develop an adaptive learning platform that provides functionalities including:

- User learning data collection and analytics;
- Determining the most suitable learning plan for learners based on AI planning or machine learning techniques;
- Providing recommendations for appropriate learning content in accordance with the learning plan.

Apparently the allocated time for developing the adaptive learning platform from scratch is insufficient. Therefore, a more feasible approach would involve exploring existing works that can be borrowed as a starting point. Figure 3.4 illustrates our preliminary plan for the thesis.

To start with, we intended to investigate various open-source e-learning platforms available on the Internet with the goal of selecting one that can create interactive content,

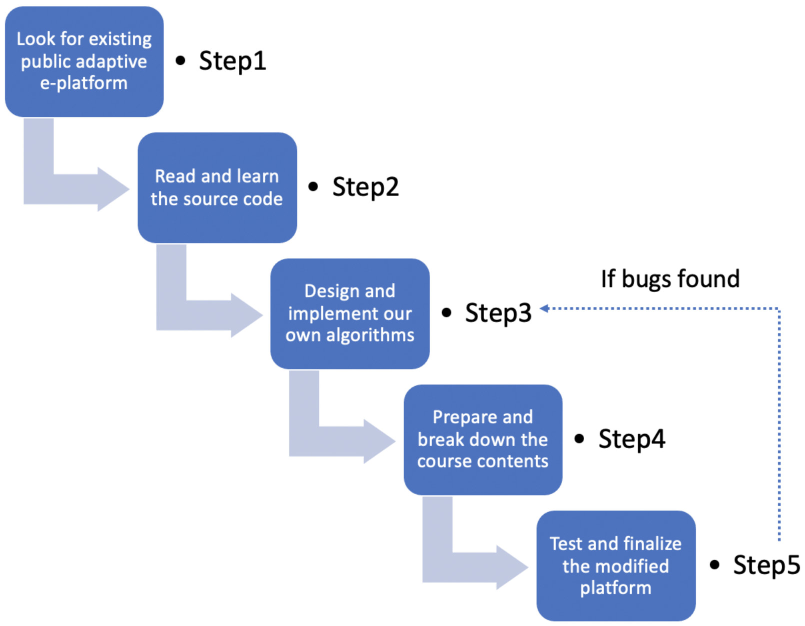

Figure 3.1: Plan for initial goal

such as slides and exercises. The reason why open-source platforms are preferred is because it provides the flexibility in customizing functionalities within the existing framework. We explored the following three platforms in our attempt:

1. Drupal
2. Open E-learning
3. Moodle

3.1.1 Drupal

Our first trial is Drupal, which is a popular content management system and widely used by many people to build their websites. The most advantage of Drupal is it offers a low learning curve and allows for the creation of websites through drag-and-drop operations.

After finishing all environmental configuration works, we tried to build a simple e-learning website via Drupal. However, there are a certain limitations of Drupal resulting a decision of discontinuing its use for our project:

- Misalignment with E-learning Platform Requirements: As a widely used content management system, Drupal offers the flexibility in content delivery and customization. However, our objective was to develop an e-learning platform specifically designed to support learning and teaching features which Drupal does not possess.
- Inconsistency with the Current Learning Management System (LMS) at UNSW: It is important for our adopted platform to be consistent with the current LMS used in UNSW. Unfortunately, Drupal is not consistent with the existing system, which could create confusion and increase the learning curve for new users to use.

Taking these shortcomings into consideration, we decided to explore alternative solutions that are more suitable for our thesis.

3.1.2 Open eLearning

Upon the recommendation of Prof. Claude, another promising application called Open eLearing became our next candidate. Open eLearning is a free and open-source software that provides flexibility and diversity in terms of creating teaching content and activities.

Different from Drupal, Open eLearning allows users to build rich and captivating courses by incorporating multimedia contents, such as text, audio and video. Another advantage of Open eLearning is it simplifies the process of creating interactive exercises and games by effortless drag-and-drop operations on the screen. The figure 3.2 shows how we made a slide within a few minutes and figure 3.3 show how we designed and customized an exercise on the interactive presentation. Notably, Open eLearning enables the attachment of remarks and score to each question, which ensures an immediate feedback could be given and greatly enhances user experience.

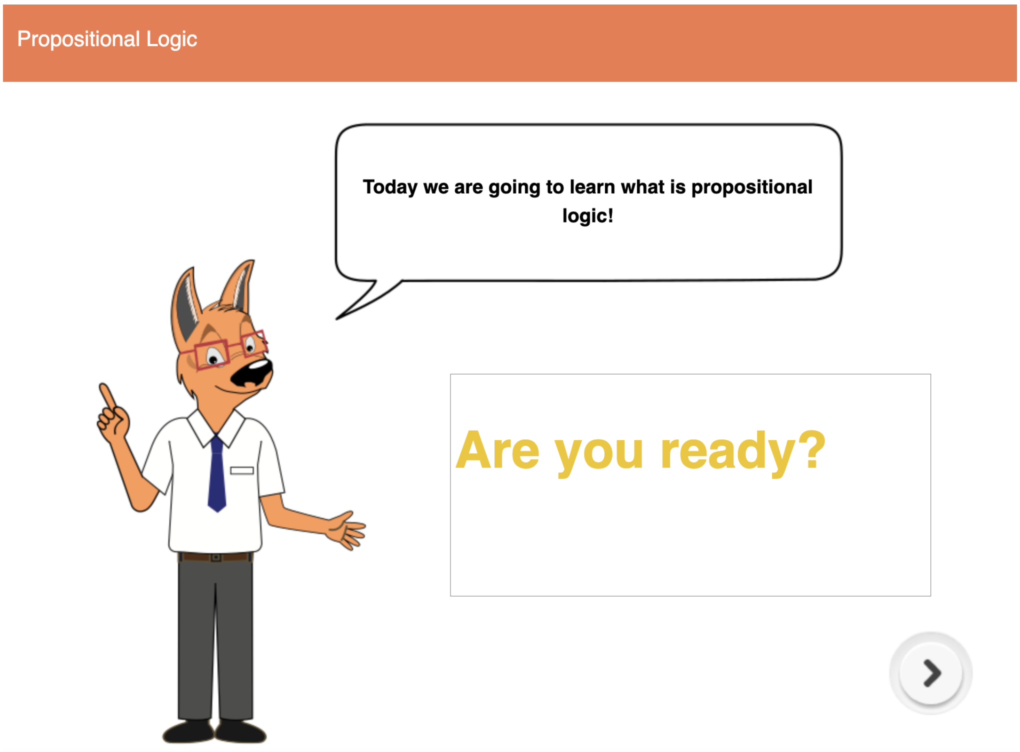

Figure 3.2: Create a slide by open eLearning

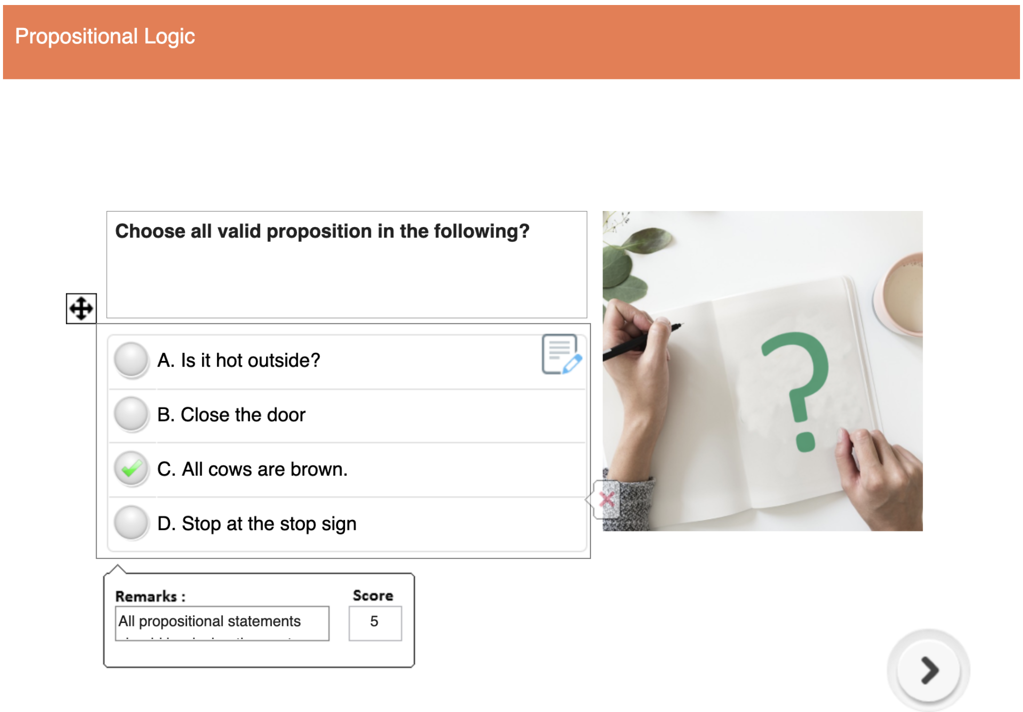

Figure 3.3: Create an exercise on a slide

Our ultimate objective was to create an system for adaptively rendering learning materials and activities rather than simple content creation. Therefore, we delved deeper into Open eLearning and examined its source code, aiming to find a way to have fine-grained control over the delivery of content at the code level.

With further exploring Open eLearning, we encountered a few challenges. The first issue was that Open eLearning was a desktop application. Although the desktop applications generally offers higher stability and better user experience they require different versions of code in order to be compatible with various operating system. This would have resulted in a significant increase in our development workload due to the need for multiple code versions.

Another challenge we encountered was the lack of robust support from the original development community for Open eLearning. Unfortunately, only a small group of people who are familiar with Open eLearning means it is impossible to gain many contributions from external developers. Furthermore, the most recent version of Open eLearning was released in 2019, and since then, it appears that the original development team has stopped updating the application. Due to the scarcity of related resources and documentation available the difficulty of development increases significantly.

In the end, considering these challenges we decided to abandon Open eLearning as an option and explore alternative platforms. Although it was finally proved that Open eLearning is not the best option for our thesis we were still beneficial from this exploration. It provided us with valuable insights and inspirations regarding the features that should be incorporated into an e-learning platform.

3.1.3 Moodle with H5P

Similar to Drupal, Moodle is another prevalent Content Management System (CMS) and functioned as a Learning Management System (LMS) by many institutions and universities like UNSW. However, Moodle also has the same drawback as Drupal that it literally serves as a content management system rather than a comprehensive e-learning system. Therefore it still lacks the robust ability to create interactive learning materials and activities like Open eLearning.

In many universities, teachers create their teaching slides on their local computers and upload these materials to Moodle as well as develop a bunch of quizzes questions for assessment purpose. In this case, learning and assessment are treated as two separate components and on different pages. Our objective was to seamlessly combine these two functions, allowing students to view slides within the application and have relevant quiz questions generated on the same page to assess their understanding of the corresponding content.

Apparently Moodle itself cannot satisfy all our requirements. In the meantime, we discovered another desirable HTML5 Plugin (H5P) which is open-source and compatible with many LMS. There are three key reasons why it is ideal for our thesis:

1. As a plugin, it can be perfectly embedded within Moodle - the existing LMS used in UNSW. This eliminates the need to introduce a new application, reducing unnecessary complexity and minimizing the learning curve for new learners.

2. Being open-source means it provides us with full control over its source code. This enables developers to modify its codes to implement adaptive recommendation of learning materials and data collections from users. Additionally, the active H5P forum and community provides a platform where we can seek assistance and guidance when needed.

3. The existing H5P enables multiple interactive content creation. With H5P, teachers gain the ability to create and edit interactive videos, presentations, games, branching scenario and more. Those developed content can be easily imported and exported to another platforms.

Addition to interactive course presentation creation, H5P provides another feature called branching scenario. By definition, branching scenarios provides users an ability to create interactive narratives where the direction and outcome of the scenario are completely determined by the learner's choices and actions made. After discussion with my supervisor, we decided to start with breaching scenario, and modify its source code allowing us to embed our own adaptive algorithm. In this way, teachers could still design and create scenarios through the user interface, while the branching logic would be determined by our custom algorithm. Therefore, after successfully deploying Moodle on our local environment and integrating H5P, we started exploring the branching scenario feature in more detailed.

However, this plan proved to be much more challenging than we expected. Despite spending a vast amount of time in looking at the source code of the branching scenario, we finally found that its functionality was sealed and encapsulated. This implies that direct modification of branching scenario source code was not possible, and the only way to achieve our goal was to write our own customized script.

As we proceeded with the development of the customized H5P script trying to access and modify the input and output of the branching scenario, we encountered another major obstacle that the customized script could not function properly on Moodle. It was a big strike to us because it means all the previous work we had done is ineffective. After spending about two third of time on Moodle and H5P, we got stuck and finally decided to give up this plan.

3.2 New thesis topic and requirement

After several trials in constructing the e-learning platform, we realized that it is necessary to pause and reconsider our thesis direction. At the same time, my another thesis partner - William Watson developed a simple but sound e-learning website that supports interactive content rendering. With discussion of my supervisor Prof. Claude, we decided to adjust thesis direction and build upon William's work. Specifically, the new direction will focus on the following key areas:

- Due to time constrain, the e-learning platform developed by William currently only supports the rendering of uploaded learning content and the generation of learning routes based on predefined problem and domain files. Therefore, further refinement of the platform is compulsory. This includes the development of a quiz system that allows teachers to design quizzes for each learning object (LO), enabling students to be tested by answering these quiz questions.

- Another important feature that needs to be implemented is the generation of prior testing before learning. When a student selects a learning object but does not satisfy its prerequisite, a series of quiz questions should be generated. All quizzes should be sourced from its pre-conditional learning objects. If the student can correctly answer all questions, the system will display the chosen learning content and mark all pre-conditional learning objects as completed. Otherwise, the student needs to go back and finish the required knowledge before being allowed to progress. In this case, students are provided with flexibility in choosing what they want to learn, eliminating unnecessary time spent on knowledge they have already possessed.
- The final objective of our thesis is curriculum design. To test effectiveness of the system, we need to select a course and break it down into a sequence of learning objects. For each learning object, it will be necessary to prepare the corresponding learning content and assessment questions.

3.3 Implementation for the new topic

After determining the new objective, we immediately started to plan our subsequent works, and the figure 3.4 depicts how we split the whole task into several subtasks and the time distributed to each subtask.

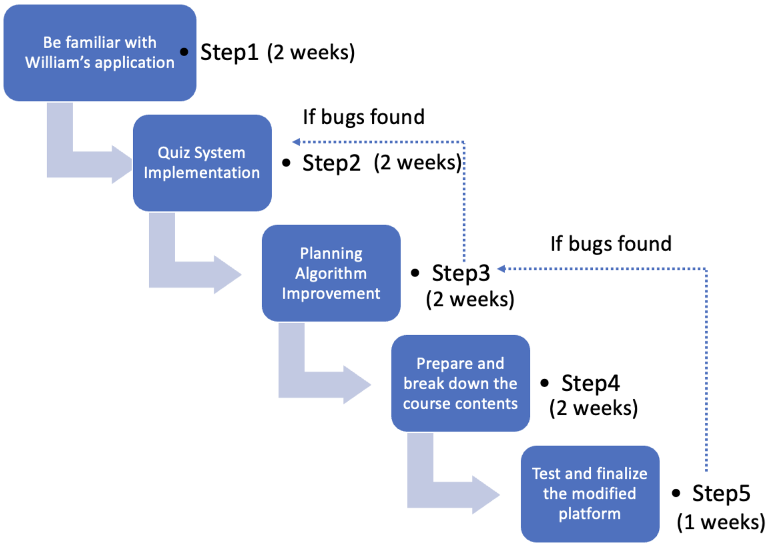

Figure 3.4: Plan for new direction

3.3.1 Implementation of quiz system

Inheriting the technology stack used by William, our implementation will still rely on MERN stack (Mongodb, Express, React and Node). Different from previous design where all created quizzes belong to one course, we decided to split the course into multiple learning objects and attach quizzes to each learning object.

As shown in figure 3.5, there are 8 learning objects are created and each learning object we create has at least one quiz. As a role of teacher, we are able to delete and edit all quiz questions.

When the learner selects a LO and starts learning, the quiz questions associated with the LO will initially remain hidden. Once the learner completes the current learning object the quiz window will then appear, prompting the learner to engage in the assessment phase. If the answer is correct, the learner will proceed to next stage learning. Otherwise, the system will present the learner with two options for further action (as shown in figure 3.6):

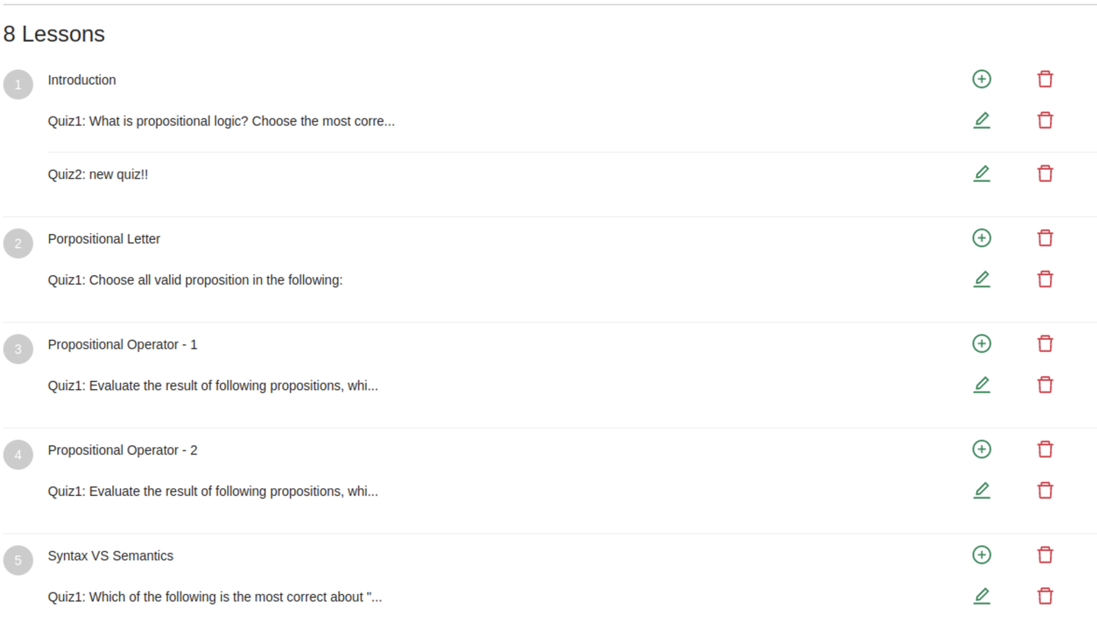

Figure 3.5: Quiz system from teacher side

1. Go back to the learning content and re-start learning again.
2. Offer more examples to the learner, where examples can be seen by clicking on the link.

For the purpose of data collection and analysis, we implemented a mechanism to record key information during the testing phase and store them in MongoDB database. The detailed data we collect is as following:

- Quiz Results: The outcome of each quiz, stored by a boolean variable which can be True or False.
- Chosen Answer: The selected answer of each quiz, stored by an array which contains A, B, C or D.

Additionally, a simple randomised algorithm had been developed when generating quiz questions. As mentioned before, one learning object may have multiple quizzes, and once the user completes a learning object, an arbitrarily quiz will be drawn by the

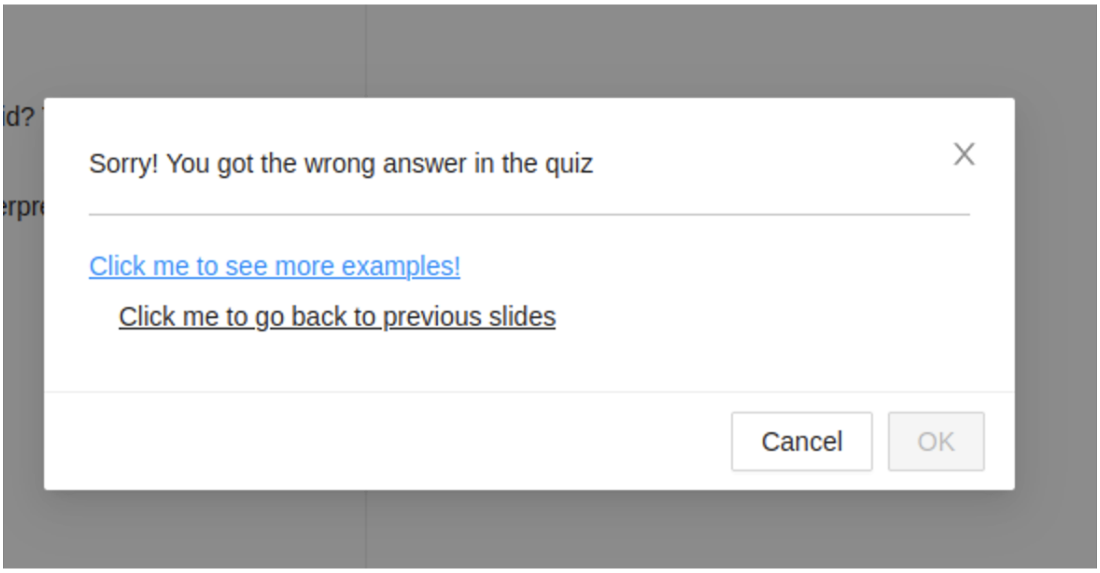

Figure 3.6: When the learner choose a wrong answer

system. By introducing this randomization feature, learners are possible to practice different quiz questions throughout their learning journey, preventing predictability and monotony of the system.

3.3.2 Implementation of dynamic learning routes generation

In the previous implementation, learners were only able to generate the learning path for the whole course, which limits their ability to start learning from a specific point within the course. This approach is clearly inefficient and a more reasonable solution should be:

1. Before initiating the learning process, learners are required to check if they have already acquired all necessary background of the course.
2. If learners confirm they have meet all prerequisites, then a simple prior testing will be given. Only when learners achieve a certain level of proficiency, are they permitted to take the course.
3. If learners intend to learn a part of the course not the whole, the system will still need to generate the most efficient learning path.

4. When learners believe they have acquired a few parts of this course and want to skip them, the system generates a test to assess their proficiency in those specific areas. The system marks the corresponding prior learning objects as completed based on their assessment result, allowing learners to proceed to the next relevant learning object. Once the status of learning objects change, the learning routes need to be re-generated by the system.

This adaptive strategy ensures that learners can make the most of their prior knowledge and only pay attention to the required areas, resulting in a more personalized and efficient learning experience. Considering time restriction, we only completed the last point in our implementation.

The figure 3.7 indicates a scenario where the learner tries to skip the first two LOs and directly study learning object of "Key Definition". The system firstly detected the leaner has not finished the learning object 1 and 2, and therefore an assessment of prior knowledge is required (figure 3.8). In the figure 3.8, there are two quizzes selected, and one is from learning object 1 and the other is from learning object 2. If the leaner can answer all of these quizzes correctly, then LO1 and LO2 are marked as finished and new learning routes will be fetched from the backend service.

For the backend system, it can be divided into two main components:

- The first part is based on Express.js framework which receives incoming request, retrieves and processes data from the MongoDB database, and sends the resulted data back to the frontend.
- The FF planner, on the other hand, is a separate component written in C and it is responsible for the optimal or sub-optimal learning routes generation. Playing a role of the third party service provider, The FF planner is called by the backend code when the frontend the signal of generating a learning path is triggered. Specifically, to initiate the learning route generation process, the backend writes the completed learning objects (initial states) and the goal state into a problem file and calls the FF planner. Then, the FF planner reads the content from the

problem file and domain file, execute its algorithm and find an optimal or sub-optimal path that transition from our initial states to the specified objectives. Finally the FF planner returns the result to backend as byte stream which will be parsed to string and sent to the frontend for display and further processing.

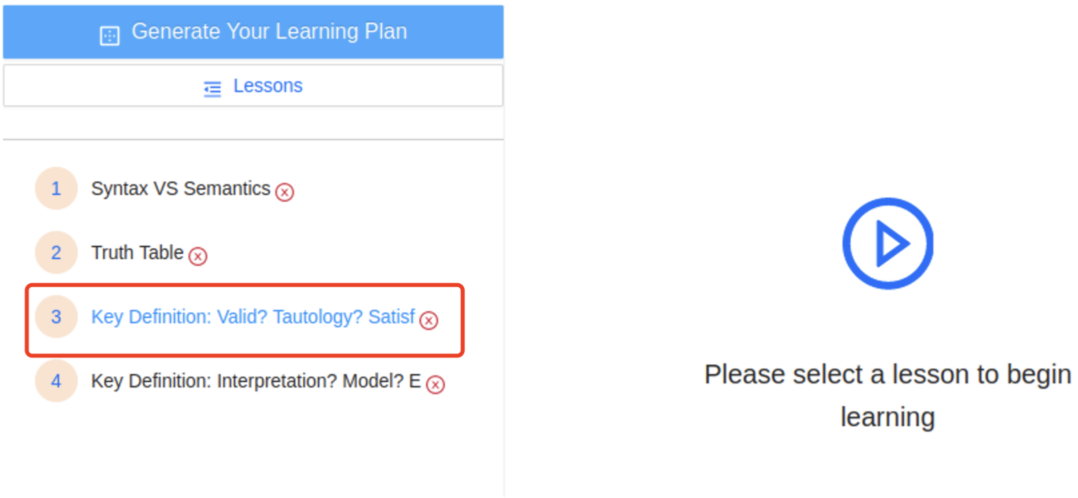

Figure 3.7: When the learner wants to skip a few LO

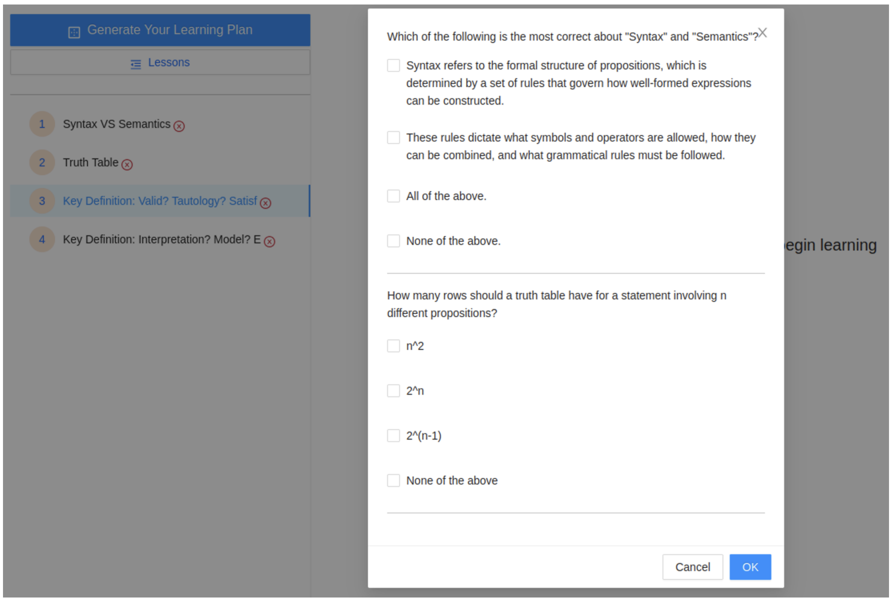

Figure 3.8: Quizzes required when skipping prior LOs

3.3.3 Curriculum design

In order to conduct a user testing, we need to design a real course content and prepare all learning materials required. Due to time constraints, we will focus on breaking down the topic of Propositional Logic from COMP3411 course into several Learning Objects (LOs) to provide a structured learning experience. The following LOs have been identified:

- Introduction (LO1): This LO will provide an overview of the topic, including any background knowledge required and the learning objectives plan to achieve in the end of course.
- Propositional Letter (LO2): This LO aims to explain the definition of propositional letter and provide precious examples that demonstrate how we can translate English sentences using propositional letters.
- Propositional connectives - Part 1 (LO3): This LO will cover the basic propositional connectives, including Negation, Conjunction, and Disjunction.
- Propositional connectives - Part 2 (LO4): This LO will focus on more complicated propositional connectives, including Implication, Bi-implication.
- Syntax and Semantics (LO5): This LO will compare the meaning of Syntax and Semantics, and how we can distinguish these two.
- Truth table (LO6): This LO will introduce the concept of a truth table and explain how we can construct one for a given expression.
- Key definition - Part 1 (LO7): This LO will provide detailed definitions and examples of important concepts in propositional logic, including tautology, satisfiability, and equivalence.
- Key definition - Part 2 (LO8): This LO will provide detailed definitions and examples of important concepts in propositional logic, including Interpretation, Model, and Entailment.

Notably, the granularity of learning objects is a challenge and requires careful consideration. It is important to keep a balance between containing detailed content of each learning object without overwhelming learners, and also ensuring that the learning objectives are adequately addressed.

After finalizing the write-up of the teaching slides for each learning object, we paired each learning object with several multiple choice questions which we modified from existing resources. In addition to quiz question design, we also need to specify precondition of each learning object:

Learning Object	Pre-condtion
LO1	None
LO2	LO1
LO3	LO2
LO4	LO3
LO5	LO1
LO6	LO4, LO5
LO7	LO6
LO8	LO7

Table 3.1: LOs and their Precondtion

Overall, teaching slides, quiz questions and precondition design are three most important components, which guarantees the effectiveness of the adaptive e-learning system.

Chapter 4

Evaluation

4.1 Developer side evaluation

Web Content Accessibility Guidelines (WCAG) are a universally recognized standard that codifies a series of testable, measurable statements called "success criteria" [3]. In this chapter, we evaluate the application based on WCAG principles.

4.1.1 Perceivability

Perceivability means content must be presentable to learners in a way they can perceive [3]. To achieve this, we prepared alternative text for all non-text objects presented to users, such as image, audio and video. In addition, we adjusted the color and layout of all content in order to make important information more perceivable to users. For example, when a teacher intends to create quiz questions, buttons in different colors are used to avoid confusion among users.

4.1.2 Operability

Operability refers to components and navigation must be easily operable [3]. In our application, we put a navigation bar on each page so that users are convenient to navigate between pages. Also, to accommodate diverse user needs our application supports keyboard interactions for most pages, ensuring users can effectively engage with the application regardless of their preferred mode of interaction.

4.1.3 Understandability

Understandability represents information and the operation of user interface must be understandable, that is, the content or operation cannot exceed their understanding [3]. Therefore, we have employed clear and meaningful icons throughout the application and ensured that all links are clickable and functional.

4.1.4 Robustness

Robustness is that content must be robust enough that it can be interpreted reliably by various browser [3]. By using React framework and Ant Design UI library, most of our features are responsive to different window size, including mobile application. Through rigorous testing, we have confirmed that our application is compatible with mainstream browsers such as Safari and Chrome.

4.1.5 Correctness

All functional requirements have been manually tested, and there is no significant bugs or issues found, which ensures the overall stability and reliability of the application. Furthermore, different problem files and domain files are used in testing planner, and it is proved that the planner can output the correct a learning path satisfying all precondtions.

4.1.6 Issues and Improvements

Throughout the thesis, there still exist several challenges and issues we encounter and need to solve if time permits.

- One major issue encountered is the system performance when testing more than four courses on the current application. The system seems to be slow when fetching and retrieving large amounts of content. Thus, the way to store data needs to be reconstructed since the existing design is not suitable for large scale learning data.
- During the thesis project, the portability issue has been identified with the current Fast Forward planner. The current version of Fast Forward planer can only compile on Linux system whilst most users are using Windows or MacOS. To ensure wider accessibility and usability, an alternative planner is required in the future.
- Another limitation of current system is the manual configuration of the domain file, which could be a challenge for people without a computer science background. Alternatively, we can add the functionality that automatically generates the domain file by the code when learning objects are created.

4.2 Results of real user testing

Due to time restriction we only invited three real users in our testing. The background of three participants are:

Name	Age	Male	Major
User 1	20	Female	Bachelor of Science (First year)
User 2	26	Female	Master of arts
User 3	24	Male	Master of IT

Table 4.1: Background of participants

All of three participants were first to learn propositional logic, and therefore they were asked to study from the LO1. Maximum of 5 attempts were given to each participant for each quiz and we recorded some key information for each participant throughout the learning:

Learning Object	Time Spent in Learning (mins)	Number of quiz attempt
LO1	4	1
LO2	4	4
LO3	6	3
LO4	16	Not Passed
LO5	3	1
LO6	13	2
LO7	11	Not Passed
LO8	12	Not Passed

Table 4.2: Learning result of User 1

Learning Object	Time Spent in Learning (mins)	Number of quiz attempt
LO1	4	2
LO2	4	3
LO3	6	Not Passed
LO4	16	Not Passed
LO5	3	1
LO6	13	Not Passed
LO7	11	Not Passed
LO8	12	Not Passed

Table 4.3: Learning result of User 2

Learning Object	Time Spent in Learning (mins)	Number of quiz attempt
LO1	3	1
LO2	4	1
LO3	5	1
LO4	8	2
LO5	3	1
LO6	7	1
LO7	13	1
LO8	11	2

Table 4.4: Learning result of User 3

Looking at these three results, we found that the participants' prior background significantly influences their learning performance. As a master of IT student, User 3 correctly answered all questions within just one or two attempts. In contrast, User 1 and User 2 felt struggling and challenging to complete all learning objects, in particular those involve complicated concepts. This observation indicates that our learning materials may not provide sufficient detail or clarity so that only learners with strongly related background can benefit from our application.

4.2.1 Feedback from participants

After user testing, we proceeded to gather some meaningful feedback from the participants as following:

- User 1: Explanation in each learning object was detailed, and given examples were useful. However, the teaching slides were perceived as dull, potentially demotivating learners. It could be more appealing if diversified elements are added such as some cartoon pictures or animations. Additionally, when it comes to some complicated concept like Entailment, more descriptions within the given examples were required.
- User 2: The entire content was still confusing after learning and the provided explanation should be more easy-to-understand. Apart from text, audio or video sometimes were necessary, and some hints could be offered in the quiz.
- User 3: Learning objects were organized reasonably whilst the slide was kind of tedious. Question type could be diversified, such as fill-in-the-blank questions.

From these valuable feedback, it is clearly that there exists significant potentials for improvement in the overall presentation and delivery of the learning materials.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

Apparently, traditional learning approach has a few shortcomings that need to solve. This thesis aims to discover those drawbacks and proposes a novel approach - an adaptive e-learning system, to resolve existing limitations in traditional learning. The research project consists of three main phases:

1. Literature review: By browsing recent papers on e-learning and adaptive learning algorithms, we were able to comprehensively understand the learning problems encountered and how adaptive learning algorithms can be applied to address these challenges. This phase helped us determine the scope and direction of the thesis - generating a suitable learning path by AI planning algorithm on the existing e-learning platform.

2. Implementation: Based on the e-learning platform made by William Watson, we implemented additional functionalities, such as integration of quiz system, and the refinement of the existing learning algorithm. The current system was enhanced to satisfy personalized learning requirements, allowing users to choose specific learning objects instead of going through the entire course.

3. User Testing: Through analyzing COMP3411 materials, we broke down "Propositional Logic" topic into smaller learning objects and prepared comprehensive learning materials, including teaching slides and exercises. Real participants were invited to engage in user testing and their feedback was collected to evaluate the effectiveness of the adaptive e-learning system.

In summary, the AI-based planning algorithm on the e-learning platform has been proved as a promising solution to solve the limitations present in traditional learning methods. By implementing adaptive learning algorithms and generating personalized learning paths, the effectiveness and efficiency of the learning process could be improved by the proposed system. The positive feedback given by participants further supports the feasibility and potential of this approach .

5.2 Future Work

Although many improvements were made on the current platform, there are still several potential areas for future enhancements:

- Prerequisite Test: When learners start learning a new course, the system should check if learners meet the required knowledge by providing appropriate quiz questions. Only learners pass the test, are they allowed to proceed learning.
- Data Collection: In addition to those intuitive data recorded by current system, it is beneficial to expand the scope of data collection by including extra information, such as time spent on each slide as well as question, and number of attempts. By analysing these data, we could have a comprehensive insights on learners' progress and behaviour.
- Scoring System: When we gain enough information, a more precious metrics to calculate the score of each quiz could be designed. The calculated score enables to reflect the effectiveness on the corresponding learning object by considering various factors, such as the proximity of chosen answers to the correct answer and

the number of attempts. This scoring system can effectively assess the learners' performance and provide distinguishable learning contents or learning paths based on their scores.

- User Experience Improvement: It could be more user-friendly if the system can visualize the progress of learning plan. This could be accomplished by adding a progress bar or visual indicators on the screen to indicate completed learning objects. In this case, learners could have a clear understanding of their progress.

- Testing: In this thesis, only a small group of user testing is conducted. However, in order to validate the effectiveness of the system, a large scale of controlled experiment is required in future development.

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Appendix 1

This appendix serves as a user manual that detailedly explains how a user could operate primary functionalities on the developed adaptive e-learning application.

A.1 Log in and Log out

The following screenshot (Figure A.1, A.2, A.3) showing how a user can log in, register, and log out the website.

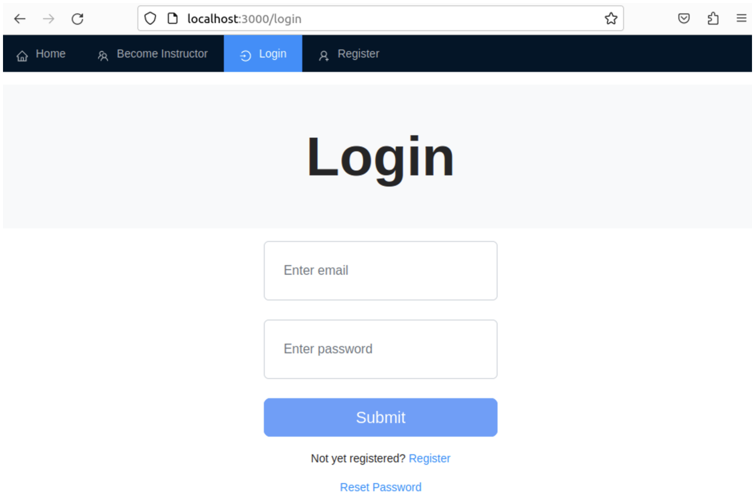

Figure A.1: User log in

A.2 Create a course

The following screenshot (Figure A.4 and A.5) showing how a teacher can create a new course.

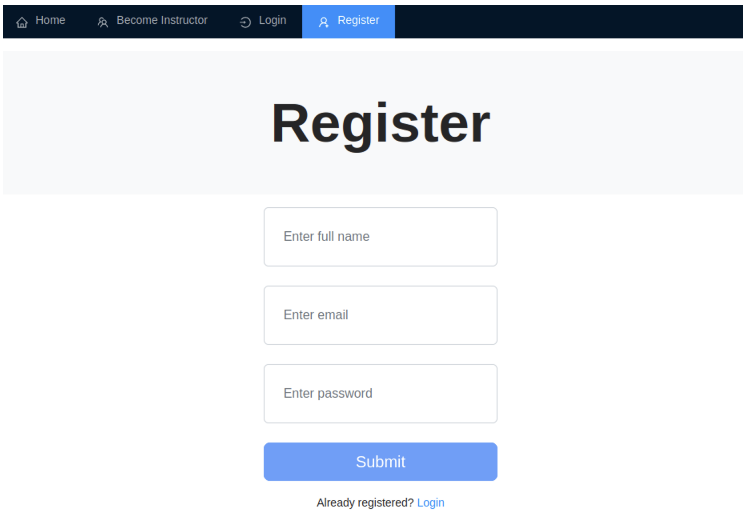

Figure A.2: User register an account

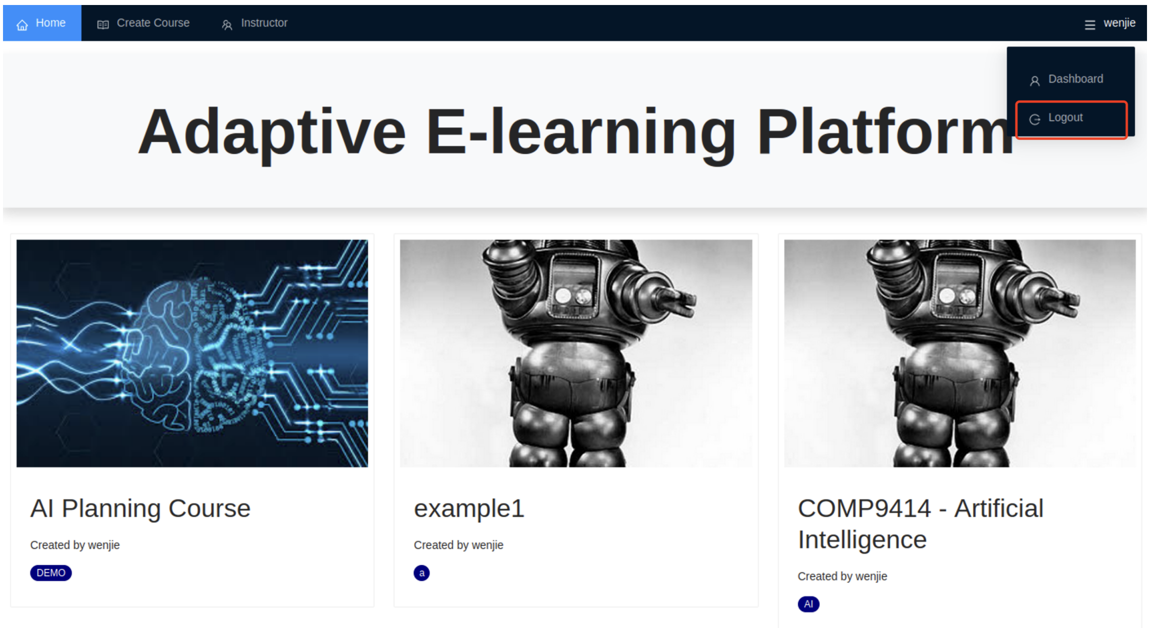

Figure A.3: User log out

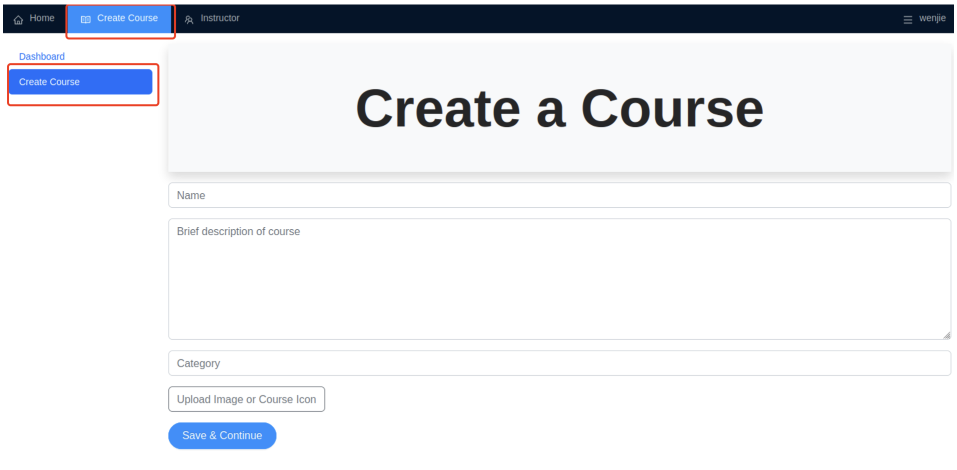

Figure A.4: Create a new course

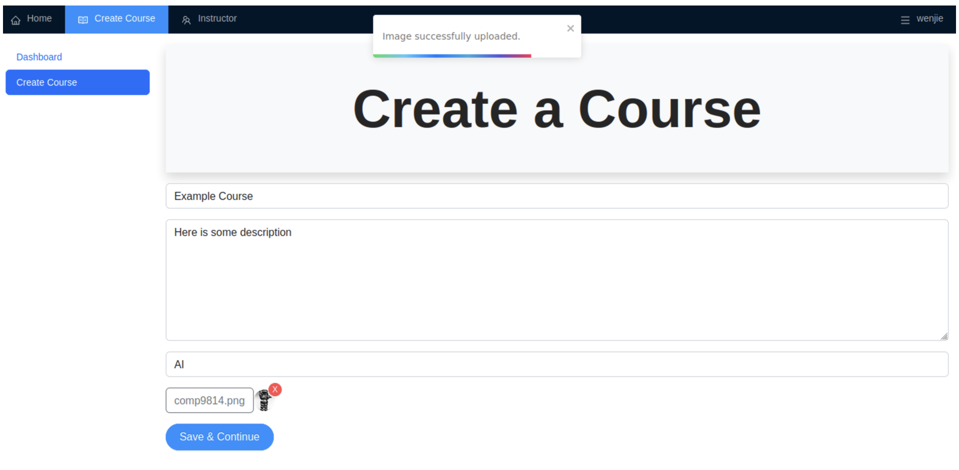

Figure A.5: Create a course with content filled in

A.3 Create a lesson

The following screenshot (Figure A.6, A.7 and A.8) showing how a teacher can create a new lesson within a course.

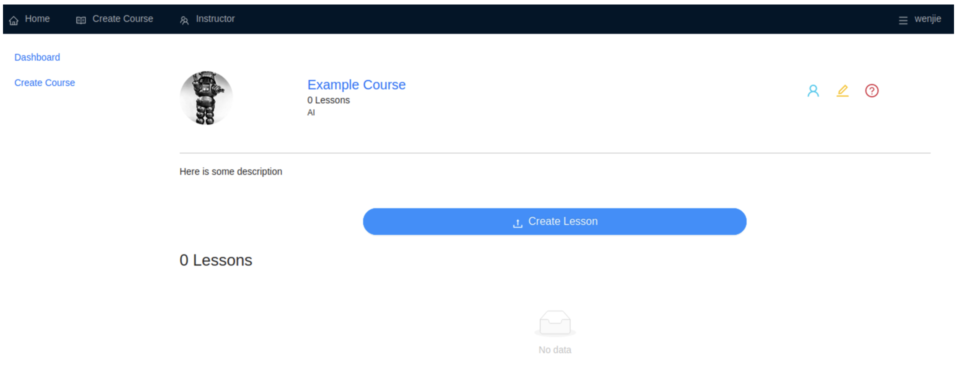

Figure A.6: Create a lesson - 1

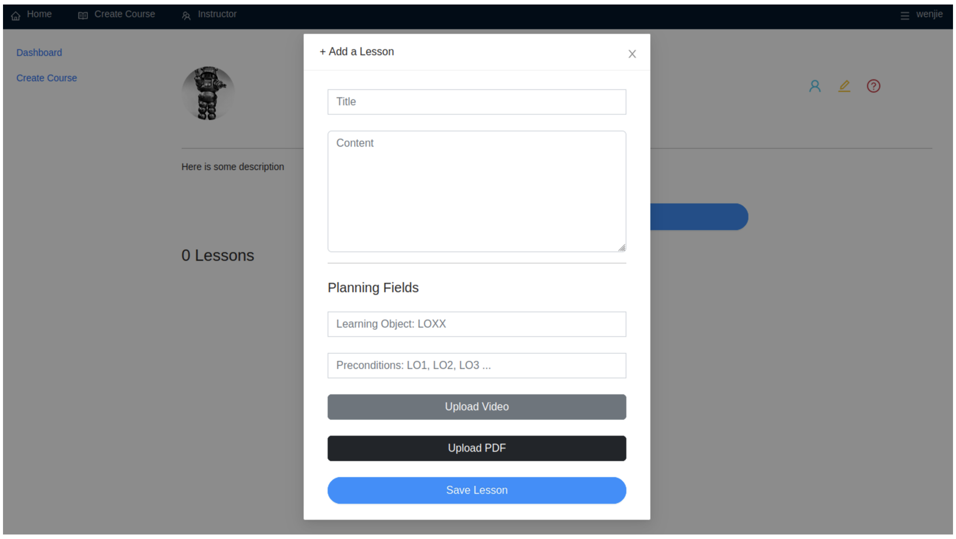

Figure A.7: Create a lesson - 2

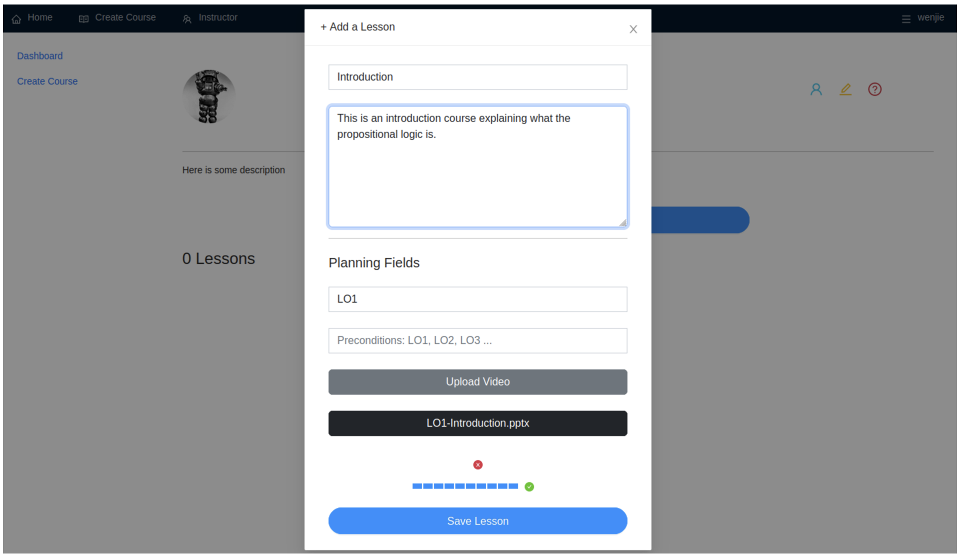

Figure A.8: Create a lesson - 3

A.4 Create a quiz

The following screenshot (Figure A.9, A.10, A.11, A.12, and A.13) showing how a teacher can create and delete a new quiz.

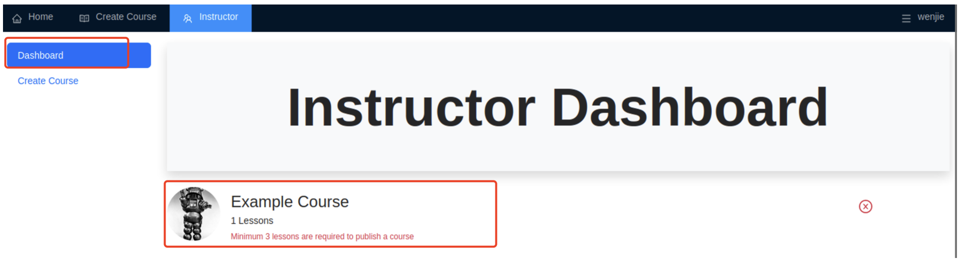

Figure A.9: Create a quiz - 1

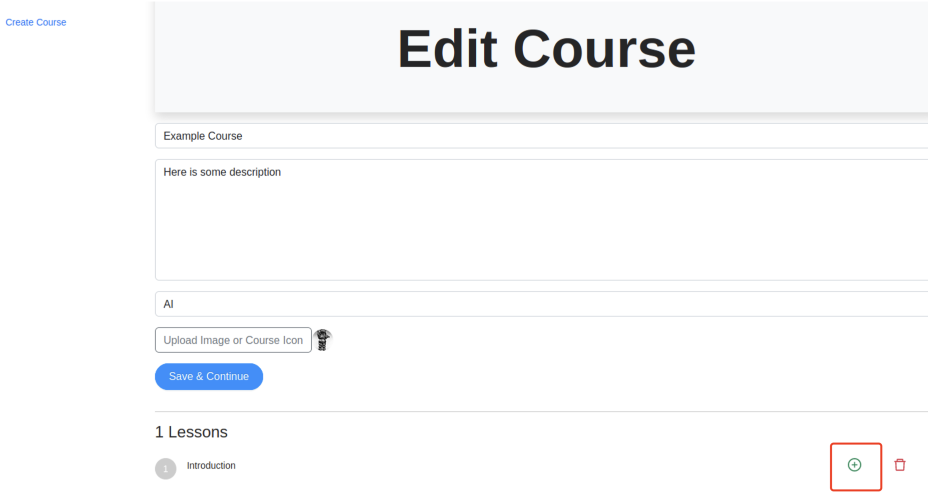

Figure A.10: Create a quiz - 2

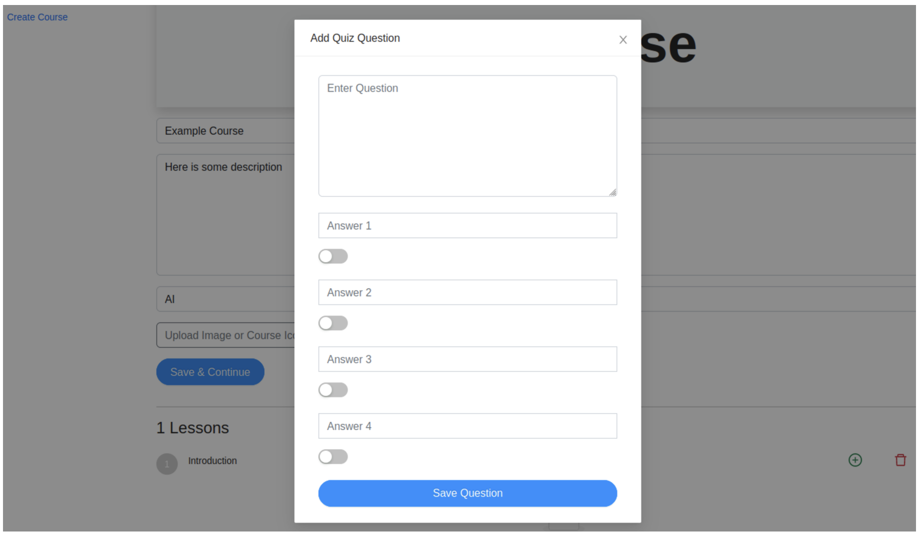

Figure A.11: Create a quiz - 3

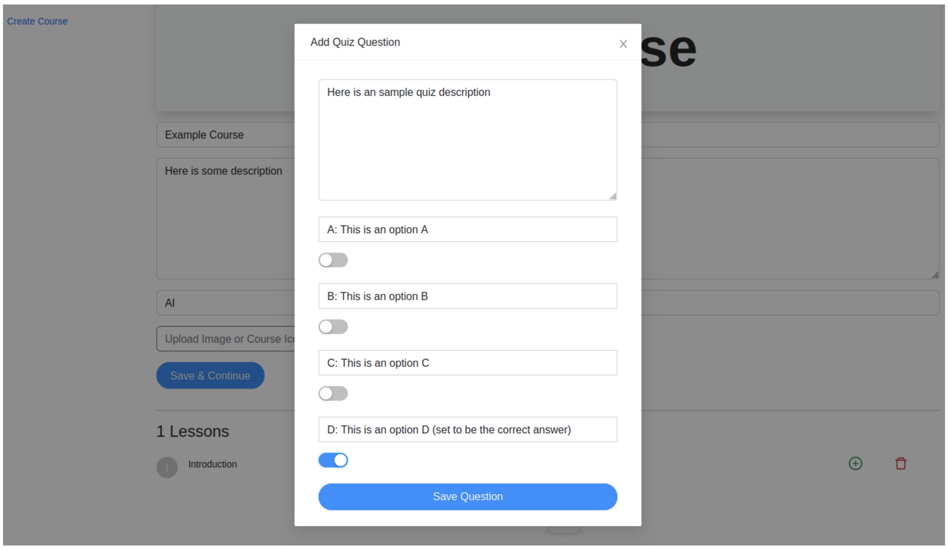

Figure A.12: Create a quiz - 4

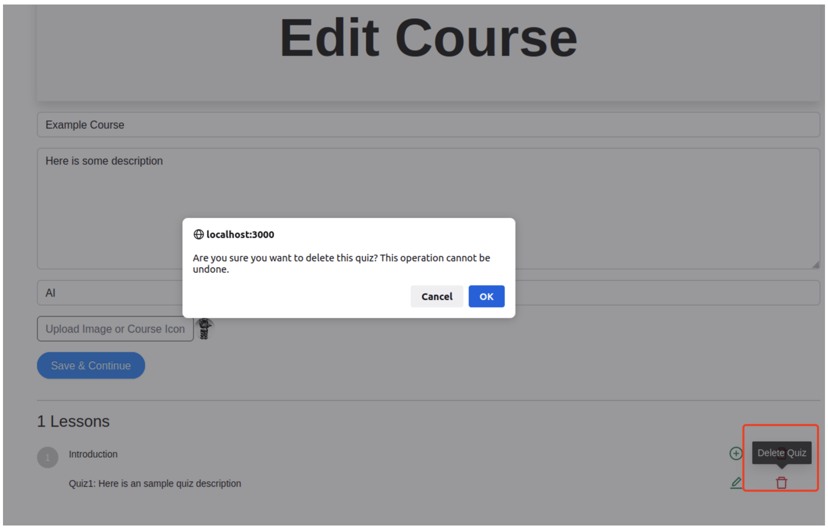

Figure A.13: Delete a quiz

A.5 Publish a course

Note that only when a course has more than 3 lessons, can a course be published, as shown in figure A.14. Once a course is published, we can see the course on the home page as shown in figure A.15.

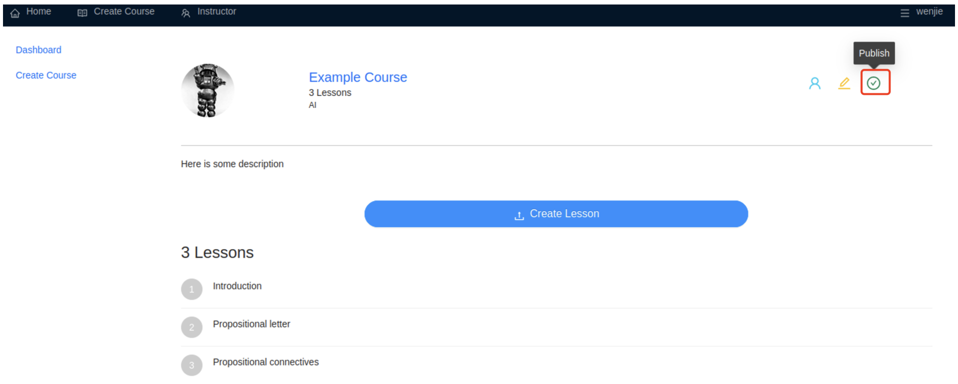

Figure A.14: Publish a course

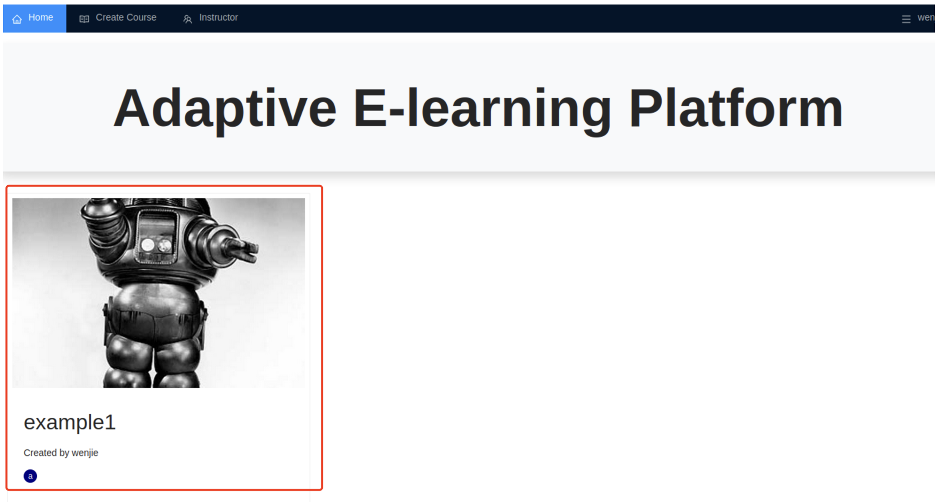

Figure A.15: Successfully publish a course

A.6 Enroll in a course

After clicking on the course on home page, an enrolling page will come out (figure A.16)

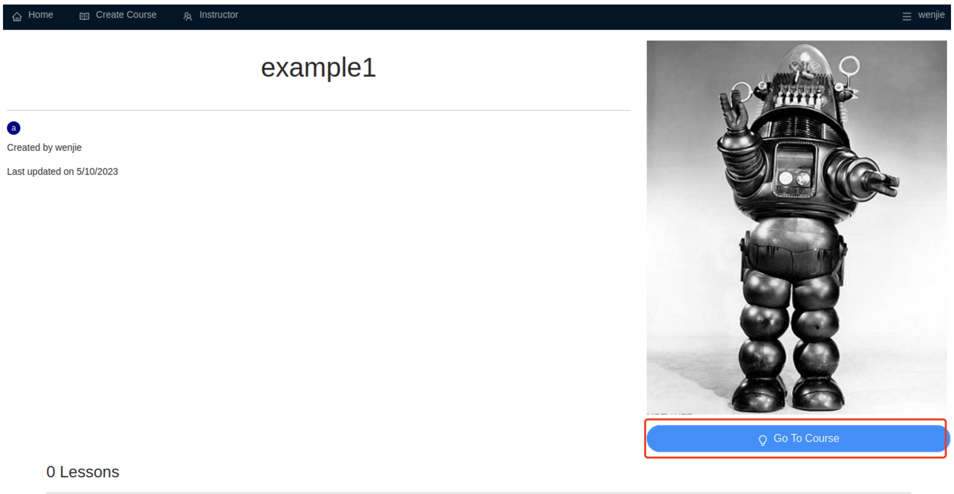

Figure A.16: Enroll in a course

A.7 Generating a learning plan

The following two figures showing how a user generates a learning plan (Figure A.17 and A.18). Here we need to note that: The learning plan is based on pre-conditions specified in the domain file. Therefore, the user currently needs to self-modify the domain file manually.

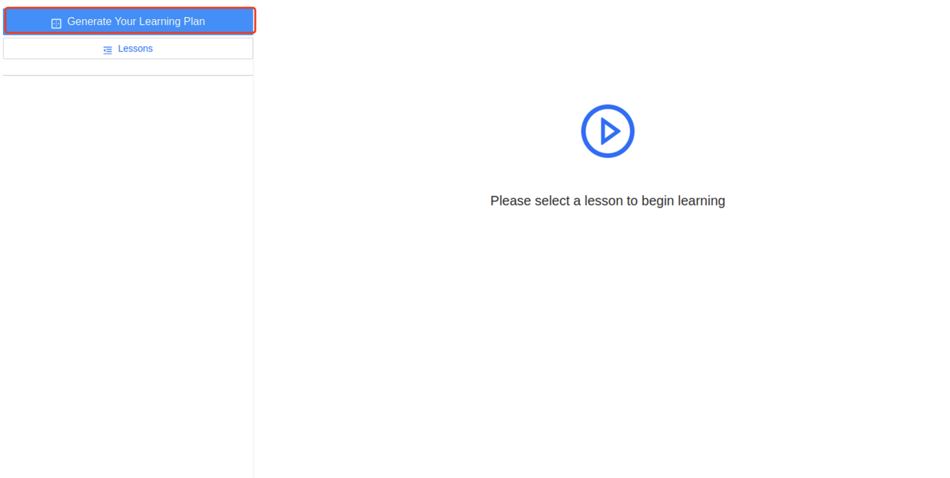

Figure A.17: Generate a learning path by clicking the button

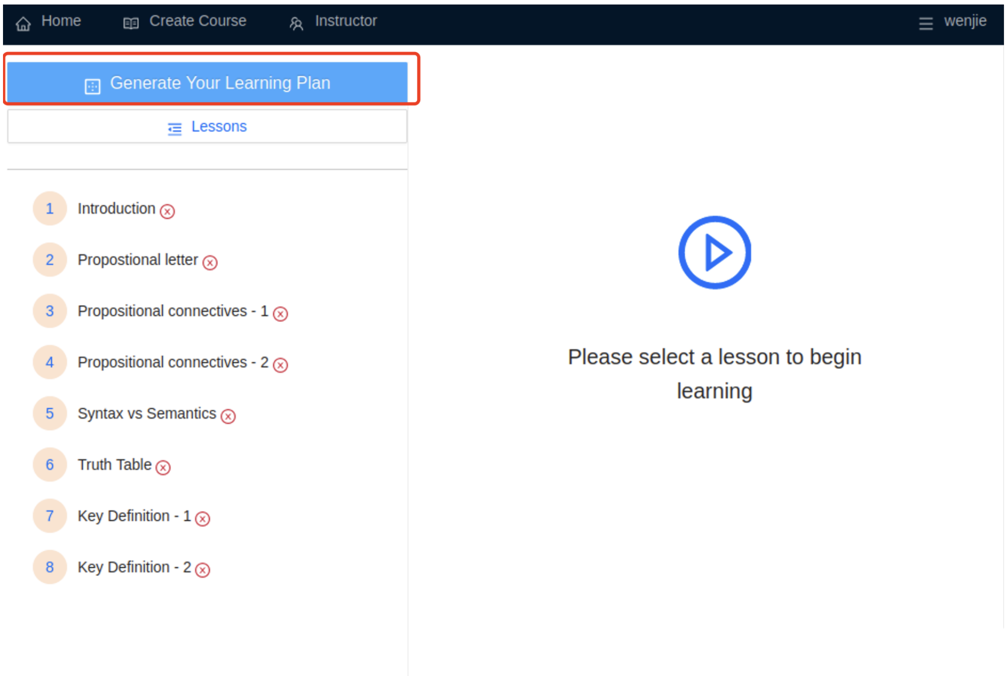

Figure A.18: Generated learning plan

A.8 Start and complete learning

Subsequently, we step into learning phase:

- A user can watch slides by clicking on the corresponding learning object (Figure A.19);
- A quiz question will pop out when reaching the last slide; The user might answer wrong answer (Figure A.22) and decides whether to go back or see more examples (Figure A.23);
- If the user get the quiz correctly (Figure A.20 and A.21), then the learning object is marked as completed (Figure A.24) and we can re-genereate a new learning plan where all completed learning objects disappear (Figure A.25);
- If the user wants to skip a few learning objects, then completing the prior test is required (Figure A.26);
- If the user passes the prior test (Figure A.27 and A.28), then all prior learning objects are marked as completed and the new learning plan is generated (Figure A.29).

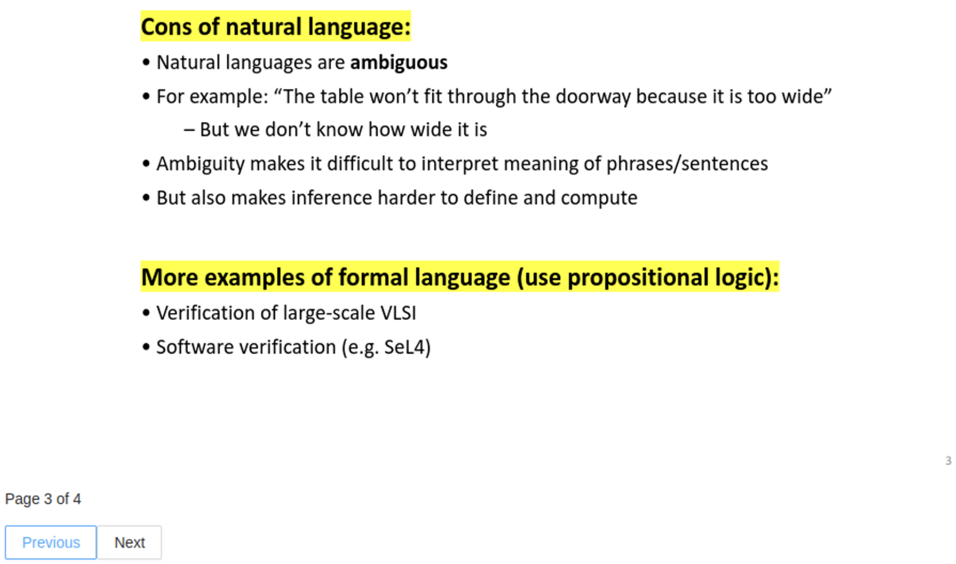

Figure A.19: Watching slides

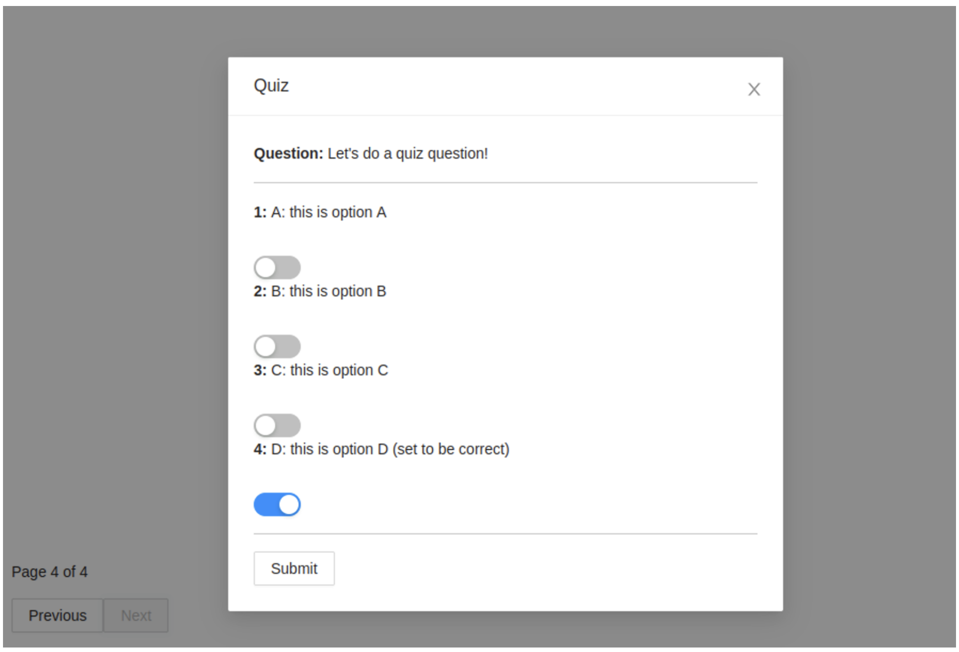

Figure A.20: correct answer

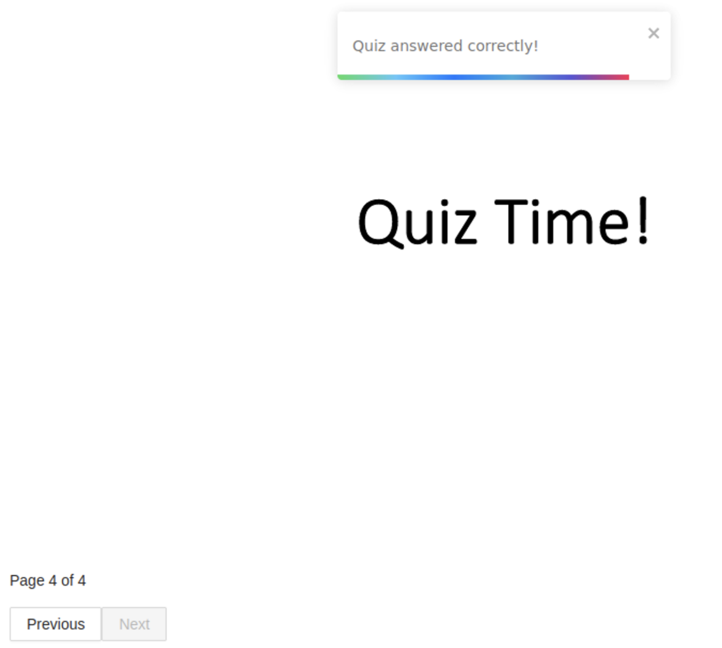

Figure A.21: correct answer - 2

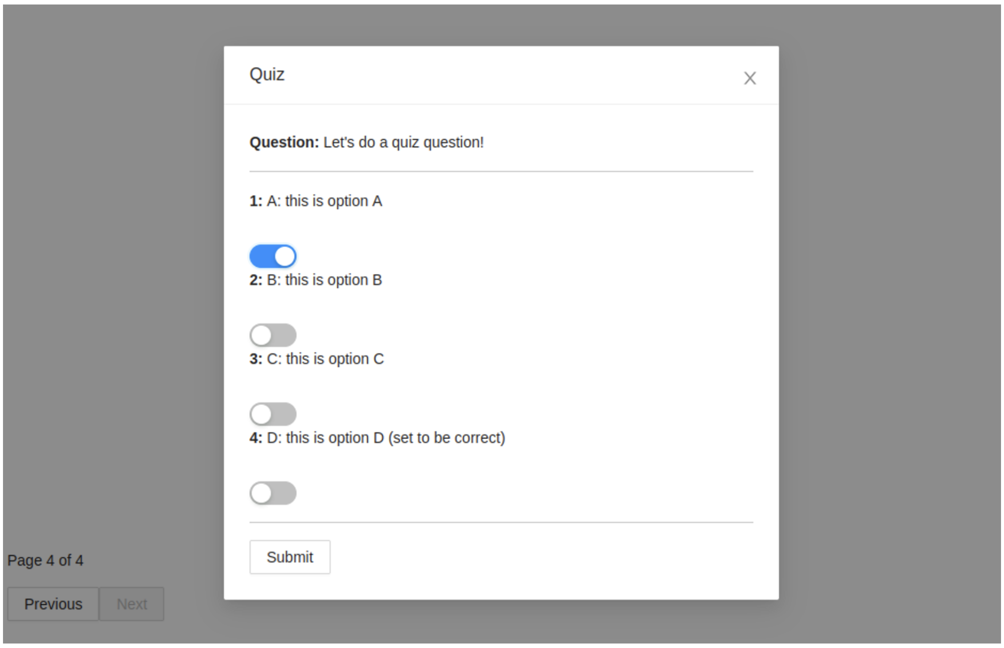

Figure A.22: wrong answer

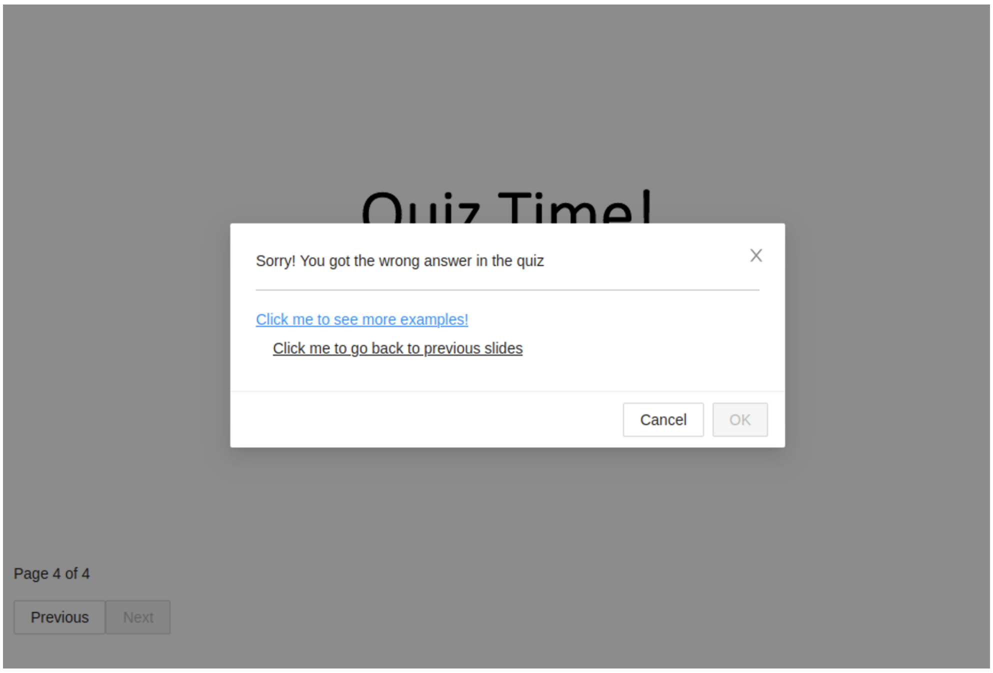

Figure A.23: Two options provided

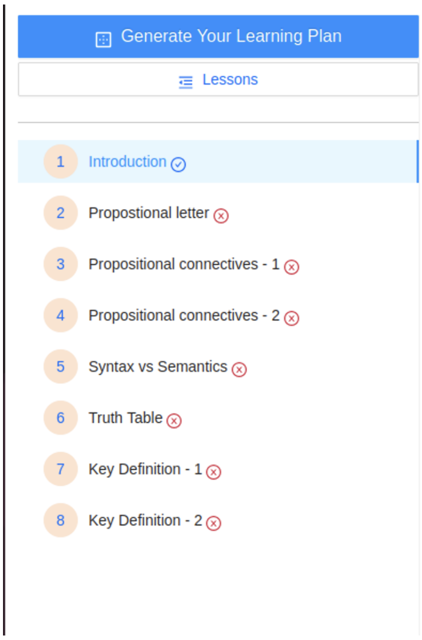

Figure A.24: LO is marked as completed

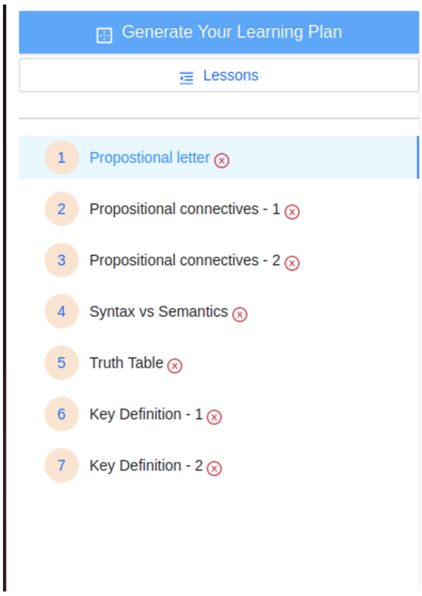

Figure A.25: New learning plan generated

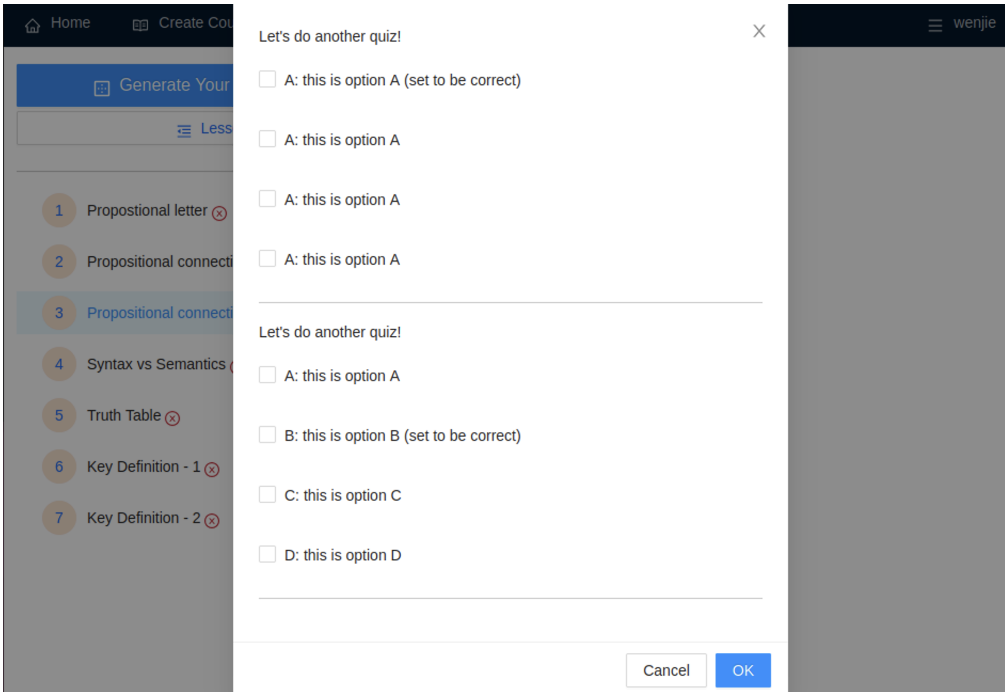

Figure A.26: Prior test

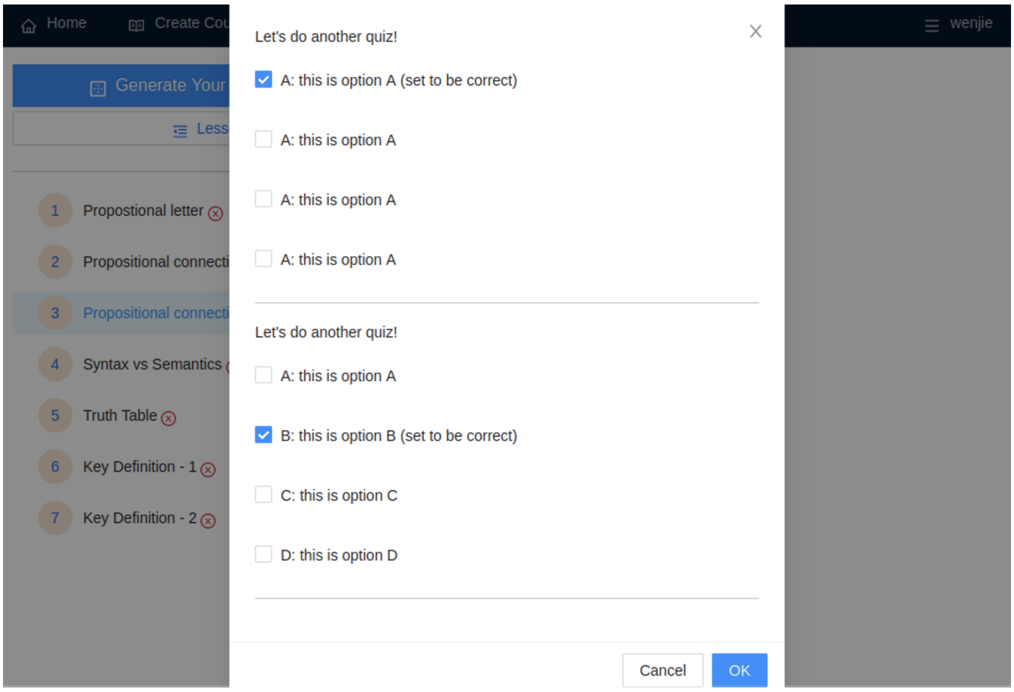

Figure A.27: Pass prior test

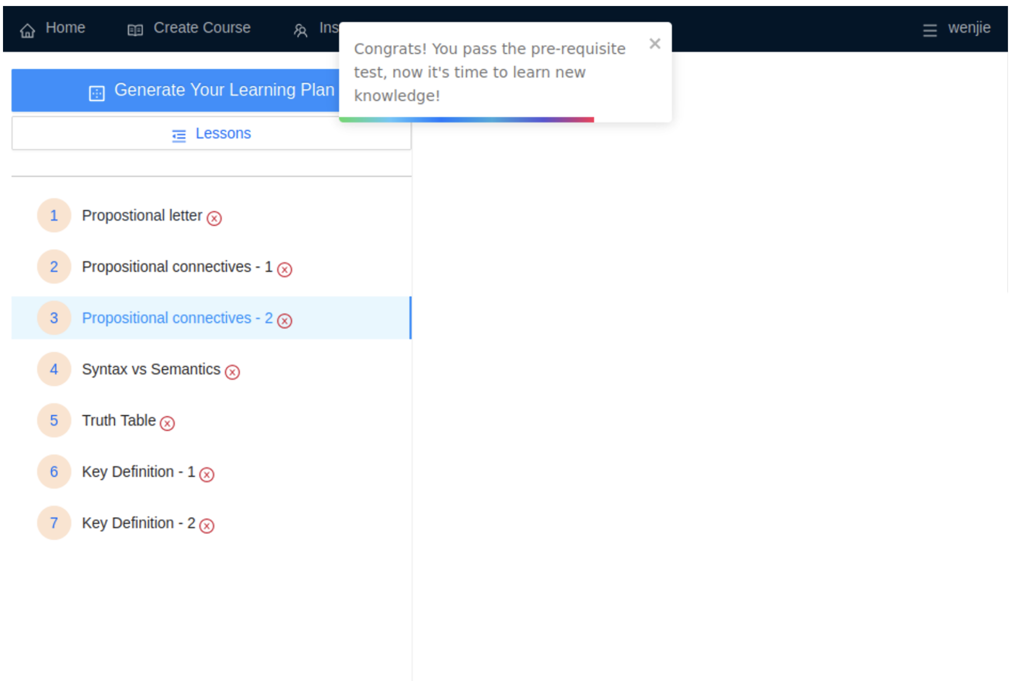

Figure A.28: Pass prior test - 2

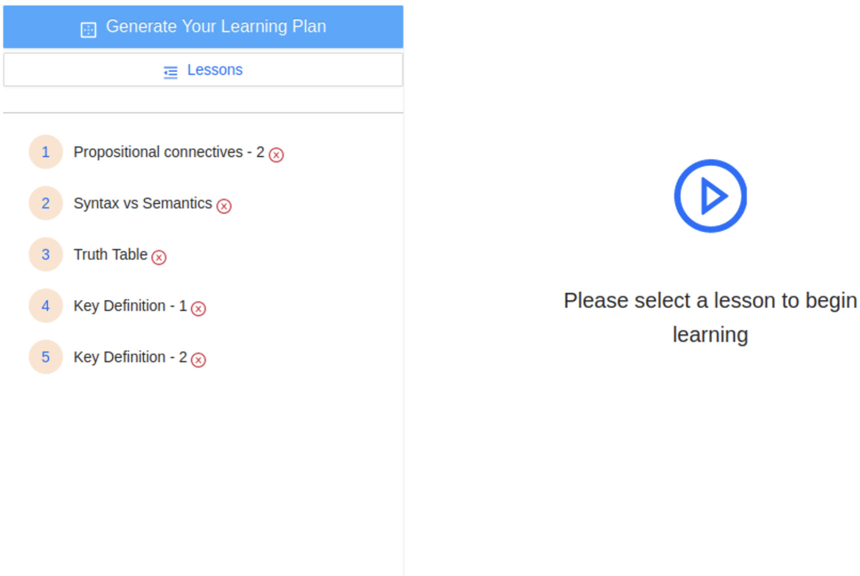

Figure A.29: New learning plan generated

Appendix 2

This appendix serves a developer guide for future developers. We will explain some key points in configuration and how to quickly get start.

B.1 Environment Configuration

To run this project, install it by following these steps in order:

1. First make sure to download MongoDB(https://www.mongodb.com/): Note that you should download MongoDB for Linux system. After the download is complete follow the setup instructions to start an instance for your specific operating system. Details of which can be found on the MongoDB website.
2. Once MongoDB has been installed and is running, make sure to connect it to your GUI of choice (e.g. Studio3T). Ensure that the DATABASE field in server/.env matches the instance you have created (Figure B.1).

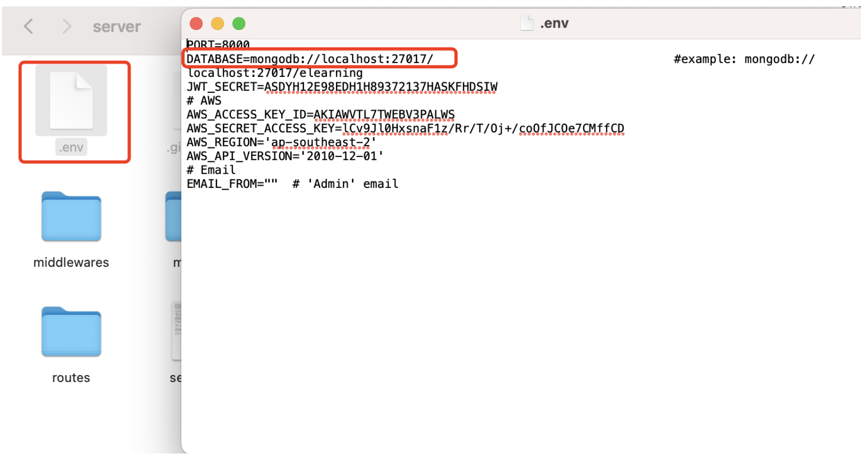

Figure B.1: Env file on server folder

3. Amazon Web Services: In order to utilise Amazon S3 for content storage and Amazon SES for mailing features the follow steps must be followed carefully:

- Create/Login a root account on Amazon Web Service Website
- Open the AWS Management Console
- Using the top search bar navigate to Amazon Simple Email Service and create an identify following the instructional video on the application page
- Once you have verified the email update the EMAIL_FROM variable in server/.env
- This will be the admin email address that any user of the platform will receieve important communications from
- Now using the top search bar again, navigate to S3 and create a bucket where content uploaded through the application will be stored
- Follow the steps for creating a bucket (The datails of properties setting can refer to Figure B.5, B.6, B.7, B.8, B.9, and B.10, and permission setting can refer to Figure B.11, B.12, and B.13).

  The Bucket policy can refer the following template:

```
{
    "Version": "2012-10-17",
    "Id": "Policy1668353125443",
    "Statement": [
        {
            "Sid": "Stmt1668353113542",
            "Effect": "Allow",
            "Principal": {
                "AWS": "arn:aws:iam::<account-id>:user/<username>"
            },
            "Action": "s3:*",
            "Resource": "arn:aws:s3:::<bucketname>"
        },
        {
            "Effect": "Allow",
            "Principal": "*",
            "Action": [
                "s3:GetObject",
                "s3:GetObjectVersion"
            ],
            "Resource": "arn:aws:s3:::<bucketname>/*"
        }
    ]
}
```

Figure B.2: S3 policy template

Policy

```
{
    "Version": "2012-10-17",
    "Id": "Policy1668353125443",
    "Statement": [
        {
            "Sid": "Stmt1668353113542",
            "Effect": "Allow",
            "Principal": {
                "AWS": "arn:aws:iam::458714226056:user/wenjie-new"
            },
            "Action": "s3:*",
            "Resource": "arn:aws:s3:::adp-learning"
        },
        {
            "Effect": "Allow",
            "Principal": "*",
            "Action": [
                "s3:GetObject",
                "s3:GetObjectVersion",
                "s3:PutObject",
                "s3:PutObjectAcl"
            ],
            "Resource": "arn:aws:s3:::adp-learning/*"
        }
    ]
}
```

Figure B.3: S3 policy example

The Cross-origin resource sharing (CORS) can refer the following template:

```
[
    {
        "AllowedHeaders": [
            "*"
        ],
        "AllowedMethods": [
            "PUT",
            "POST",
            "DELETE"
        ],
        "AllowedOrigins": [
            "http://www.example1.com"
        ],
        "ExposeHeaders": []
    },
    {
        "AllowedHeaders": [
            "*"
        ],
        "AllowedMethods": [
            "PUT",
            "POST",
            "DELETE"
        ],
        "AllowedOrigins": [
            "http://www.example2.com"
        ],
        "ExposeHeaders": []
    },
    {
        "AllowedHeaders": [],
        "AllowedMethods": [
            "GET"
        ],
        "AllowedOrigins": [
            "*"
        ],
        "ExposeHeaders": []
    }
]
```

Figure B.4: S3 CORS example

- Make sure to update the relevant AWS fields in server/.env with the information you are provided whilst setting up the bucket. Note the secret access key must be stored and saved somewhere safe at this point
- If you are stuck at any point during this setup, make sure that you are entering the fields correctly as above and have updated the relevant fields in the env files.
- Note: AWS has very detailed user guides for running through any issues here so make sure to refer to them if your requirements change and you wish to update the permissions or properties of your bucket.

4. Now, it is time to run our client in the freshly cloned project directory 'adaptive-elearning'. You can run the client by entering the following command:

```
cd client
npm install
npm run build
npm run dev (or if moving to production mode run npm start)
```

5. The client will now be running on http://localhost:3000 (You may change the port from 3000 in client/server.js if desired)

6. Now open another terminal and make sure you are in the "adaptive-elearning" directory (https://github.com/Wenjiew1996/adaptive-elearning). You can run the server by entering the following command:

```
cd server
npm install
npm start
```

7. The server will now be running http://localhost:8000 (The port may be changed in server/.env if desired)

8. FF-X (Fast-Forward Planner): The application's AI planning capabilities are configured to run using FF-X. Note that this planner is written in C and will only run on Linux Operating Systems (Developed for Ubuntu 20.04.5), and some versions of Windows - it does not compile on any versions of MacOS. To ensure smooth running of the application please follow these steps to ensure that FF is compatabile with your OS.
   Important: You don't have to run the FF Planner alone, intead, your server code will call FF planner to execute. If you still want to run it, you can type the following command (in the "adaptive-elearning" directory):

```
cd server/FF
make clean
make
```

9. Now the client and server should both be running and configured for your personal environment it is time to navigate to http://localhost:3000 and interact with the application.

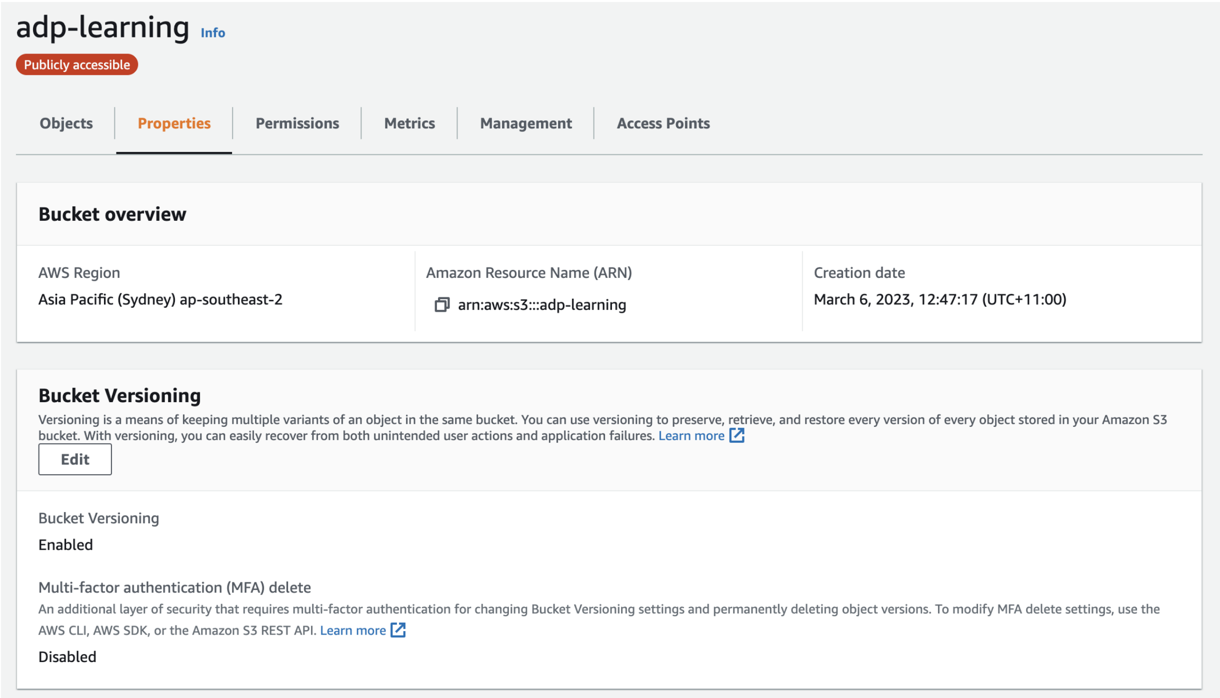

Figure B.5: S3 Property setting 1

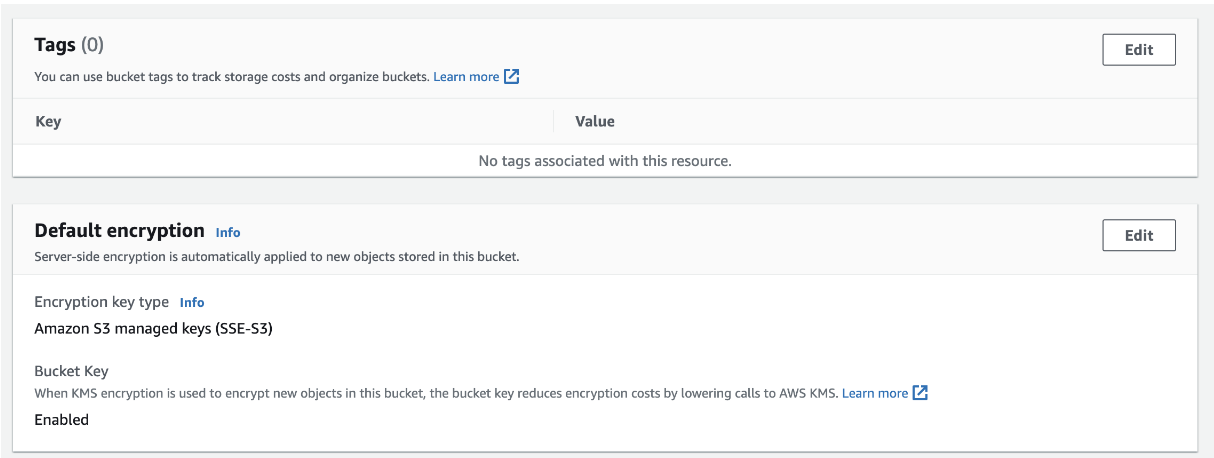

Figure B.6: S3 Property setting 2

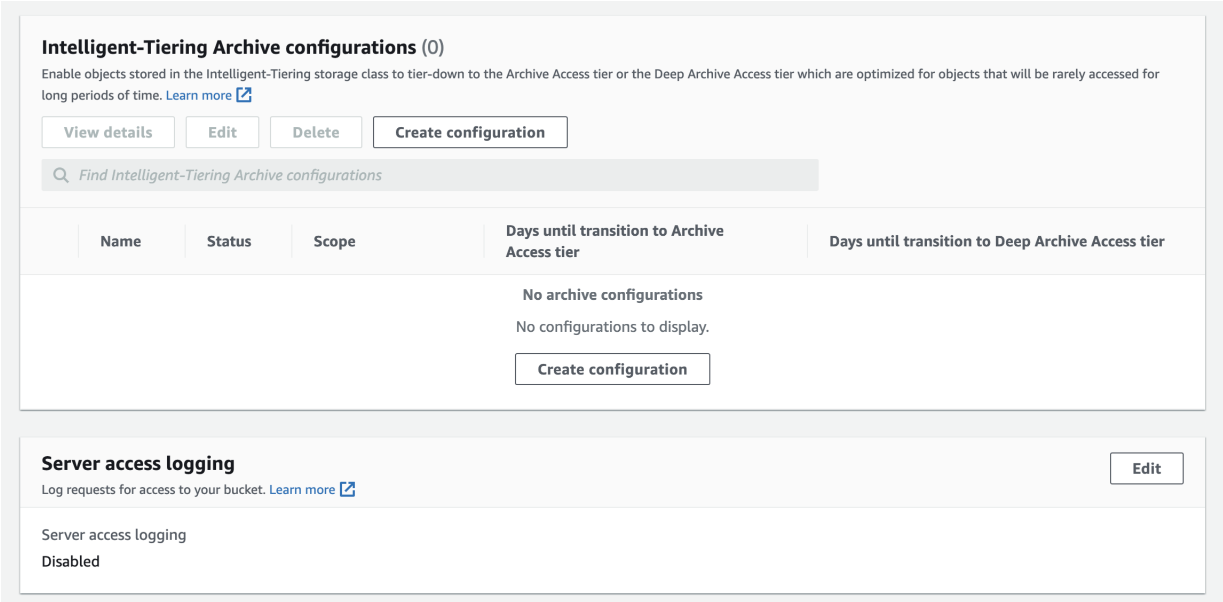

Figure B.7: S3 Property setting 3

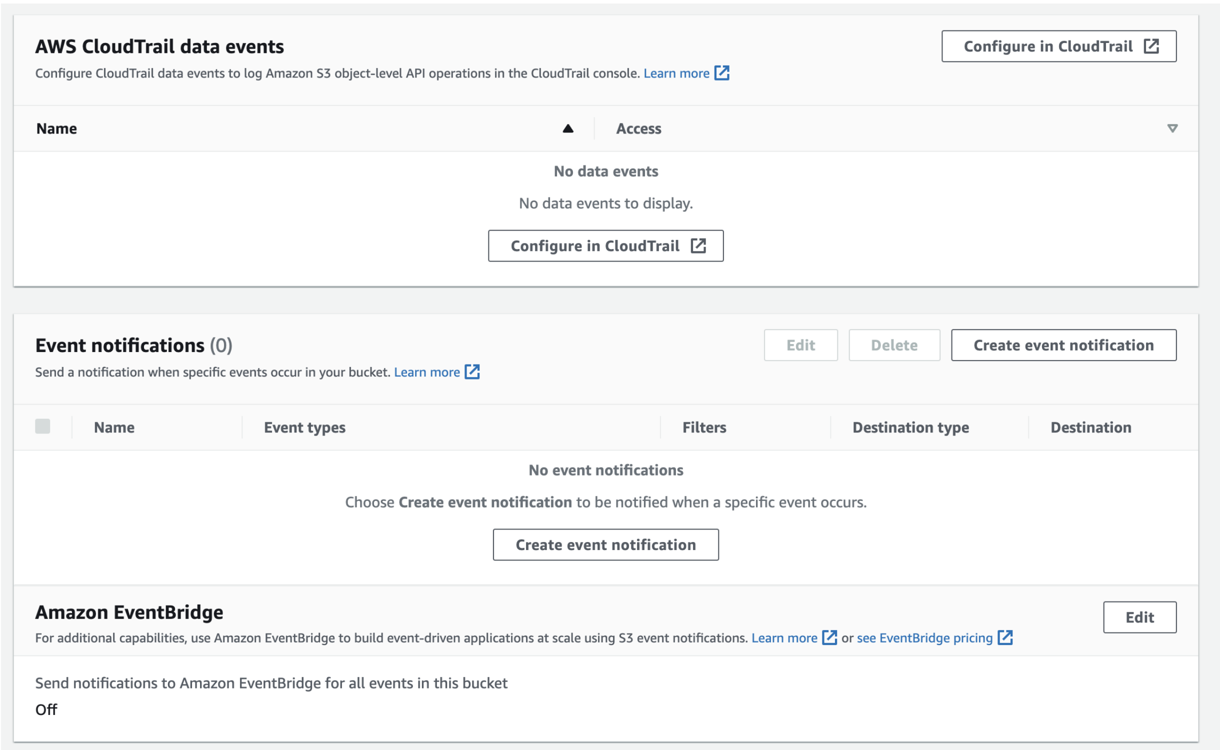

Figure B.8: S3 Property setting 4

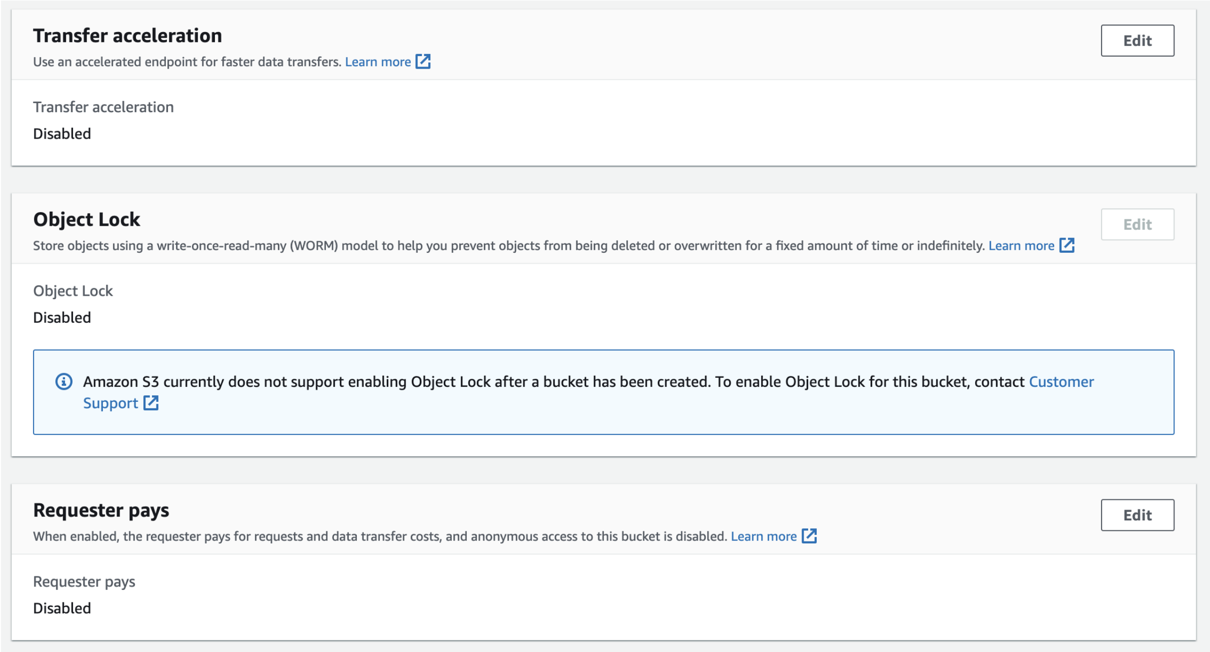

Figure B.9: S3 Property setting 5

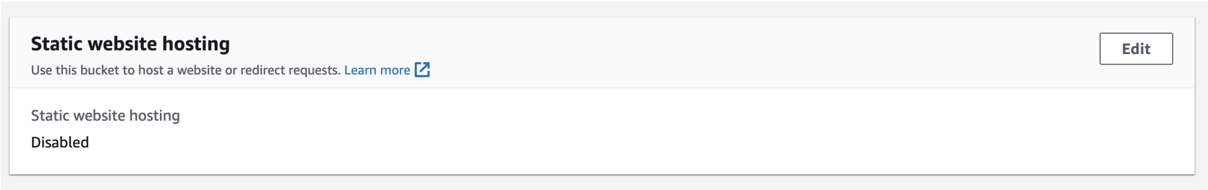

Figure B.10: S3 Property setting 6

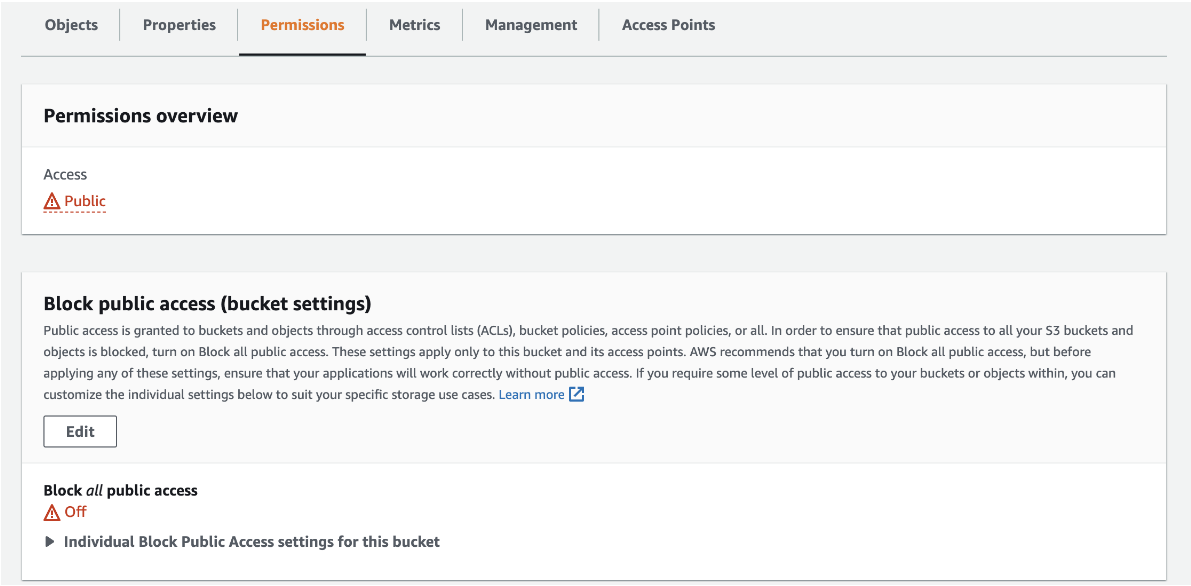

Figure B.11: S3 Permission setting 1

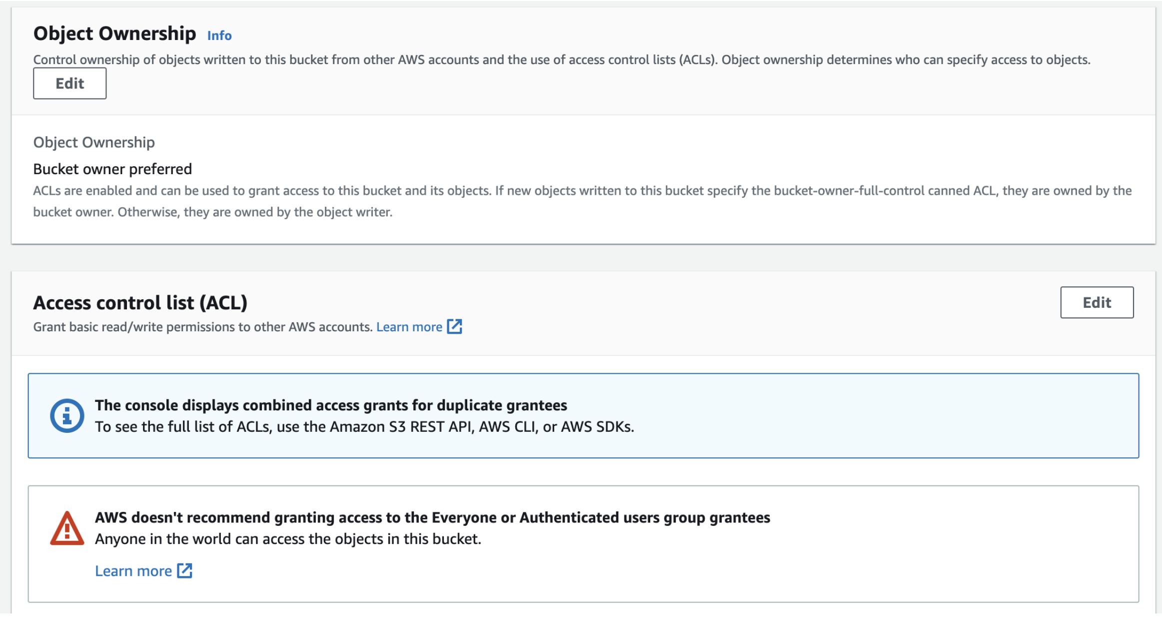

Figure B.12: S3 Permission setting 2

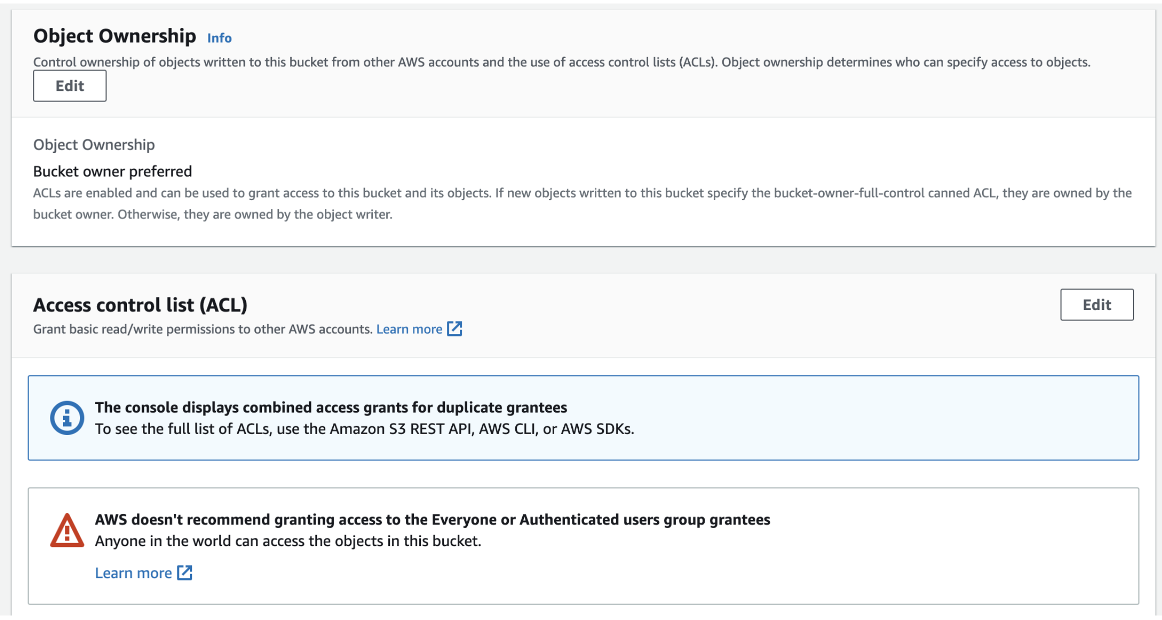

Figure B.13: S3 Permission setting 3