Generated Adaptive Learning Material (GALMAT)

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CCS CONCEPTS

• **Computing methodologies** → Artificial intelligence → Machine Learning • **Applied computing** → Education • **Theory of computation** → Formal languages and automa theory → Design and analysis of algorithms

KEYWORDS

E-Learning, Ontology, AQG, Adaptive learning, NLGA

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1 PROJECT DESCRIPTION

1.1 INTRODUCTION

Static learning is the traditional form of learning that occurs within most educational facilities today. This is problematic, as static learning comes with a "one size fits all" policy. Static learning provides the same educational materials to all students studying a particular course or topic, which provides a learner with a fundamental understanding of a topic. However, it may be considered a disadvantage in the later stages of learning as the learning content is not tailored to each individual learner. It is important to understand that each individual learner is unique; thus, each of them will learn content differently and at different paces. Static learning does not take this into account, which significantly reduces the optimal learning potential of learners.

A potential method to maximise the learning potential of a learner is to use a technique known as adaptive learning [6]. Adaptive learning is a technique whereby each individual learner is presented with a unique set of learning materials, each of which is tailored to the learner based on their academic ability. Adaptive learning identifies the knowledge gaps of a learner and then generates and presents learning materials that fill in these knowledge gaps. An ontology will be used as a knowledge base which would contain data about the domain of interest. Ontologies allow us to store data in a structural manner and the relationships between classes and properties within it. This makes searching and retrieving information easier and faster [15].

1.2 IMPORTANCE

The fundamental problem with static learning is that knowledge gaps in learners are not necessarily filled. Adaptive Learning aims to address this problem by ensuring that each learner using the system receives unique learning materials to include specific information on topics that they do not fully understand.

1.3 ISSUES

There are several issues with current Adaptive Learning systems that arise from techniques used to implement the adaptive system. The most important issue to address is the production of unreliable learning paths from the adaptive system. A learning path is essentially the different learning materials that will be presented to a learner along their journey. Thus, an unreliable learning path is a scenario when the learner will be presented learning materials that are not relevant to them along their journey. Pythagoras Karampiperis et al. [14] presents this issue of producing an unreliable learning path when the knowledge domain becomes too broad. This may result in inaccurate materials generated for the learner. Secondly, Adaptive Learning systems do not typically consider a learner's learning style - which is fundamental to the optimal learning success of a learner [4]. A learner's learning style includes aspects such as whether they are a visual learner or not, as well as how fast or slow of a learner they are. An observation can be made that Adaptive Learning systems are under-researched and that there is not an abundance of use-cases of their existence in real world scenarios [6]. Thus, our conducted research will seek to contribute to the growing research on Adaptive Learning systems.

2 PROBLEM STATEMENT/RESEARCH QUESTION/AIMS

2.1 PROBLEM STATEMENT

Continuous research has been done on adaptive learning systems and has become more prominent with the rise of e-learning. Typical adaptive learning systems do not seamlessly integrate the use of an automatic question generation (AQG) algorithm into the entire system. AQG is a key component of adaptive learning systems, as it is a technique that is used to assess a learner's knowledge. Most adaptive learning systems store information on the learner in some form of structured knowledge. For the system to be useful to the learner, feedback must be given. This means that the information stored in structured knowledge must be verbalised in a human-

readable language. Most systems do not produce a unique, detailed, and topic-relevant text document.
Furthermore, most adaptive e-learning systems that cover a broad knowledge domain use techniques to identify learner knowledge gaps, which results in the system producing inaccurate educational resources that lead a learner down an incorrect learning path [17].

2.2 RESEARCH AIMS

2.2.1. Identify what are the existing methods for accurately generating adaptive questions for a learner using their previous answers as input, and then devise an improved algorithm that increases question accuracy and suitability to a learner.

2.2.2. Develop an ontology-based adaptive learning system to accurately detect a learner's inadequate comprehension of a concept(s).

2.2.3. Investigate which method can be used for knowledge graph-to-text generation so that a document more detailed, focused on the content, and closer to a human-written one is produced.

2.2.4. Create an adaptive learning system that improves existing systems by effectively identifying and filling in knowledge gaps using previous findings.

3 PROCEDURES AND METHODS

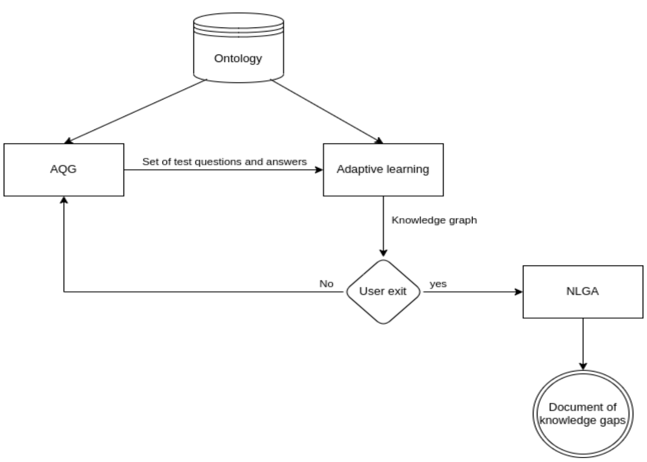

Figure 1: Abstract Representation of the System

3.1 ADAPTIVE QUESTION GENERATION ALGORITHM

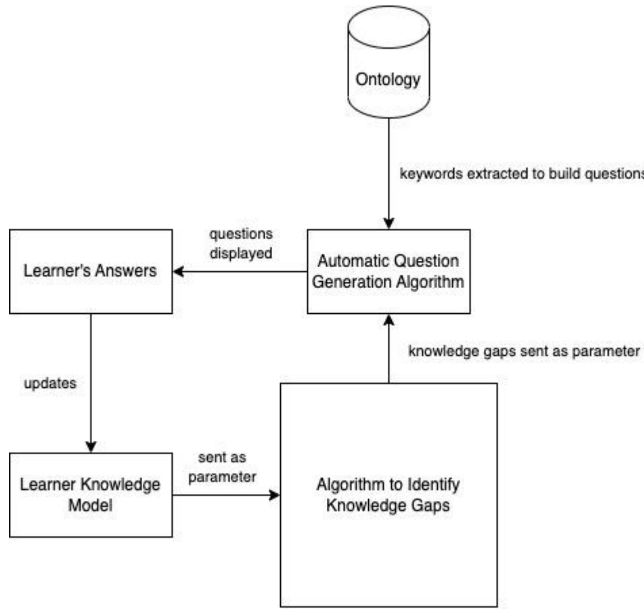

Figure 2: Adaptive Question Generation Process Diagram

A core component of the overall proposed project is the adaptive automatic question generation algorithm. This algorithm will need to initially display a set of standardised questions to a learner that uses the application for the first time. Once the user returns to the learning content (and opts to exit the testing section), the adaptive aspect of the algorithm will begin. The next time that the user returns to the testing section, questions will be automatically and adaptively generated based on the identified knowledge gaps found using the learner's previous answers. Thus, the algorithm must consult a data structure, known as a knowledge graph, before generating any questions after the initial set of standardised questions have been answered.

The knowledge graph is created using another structure known as a learner knowledge model. The learner knowledge model is created and updated within the AQG component, and it will contain the learner's question and answer pairs. The learner knowledge model will be formatted in a manner suitable for the next component, to ensure that integration is seamless between the two modules. The learner knowledge model is an important input into the next component and thus, ensuring that it is in a suitable format is optimal.

To create this, Computerised Adaptive Testing (CAT) will be used as a foundation. The newly created algorithm will seek to improve and tailor CAT to smoothly integrate within the proposed adaptive learning system. The improvements that will be made to CAT will consist of generating more relevant and accurate questions for learners using their identified knowledge gaps. A problem with CAT is that it was designed for one-time testing, which is not ideal for an Adaptive Learning System [19]. Thus, the improved AQG will be designed for continuous assessment that will be able to assess a learner's progress over their entire time of using the application.

The AQG algorithm will be evaluated by teachers and lecturers within the educational field. These individuals will be provided with the AQG algorithm and will test its ability to produce viable questions. Each question generated by the algorithm will be assigned to a category such as 'viable' or 'non-viable'. A viable question would be one that is both accurate and relevant to a learner. At the end of the evaluation, the totals of each category will be tallied to provide an indication of the quality of the AQG algorithm.

3.2 ADAPTIVE LEARNING SYSTEM

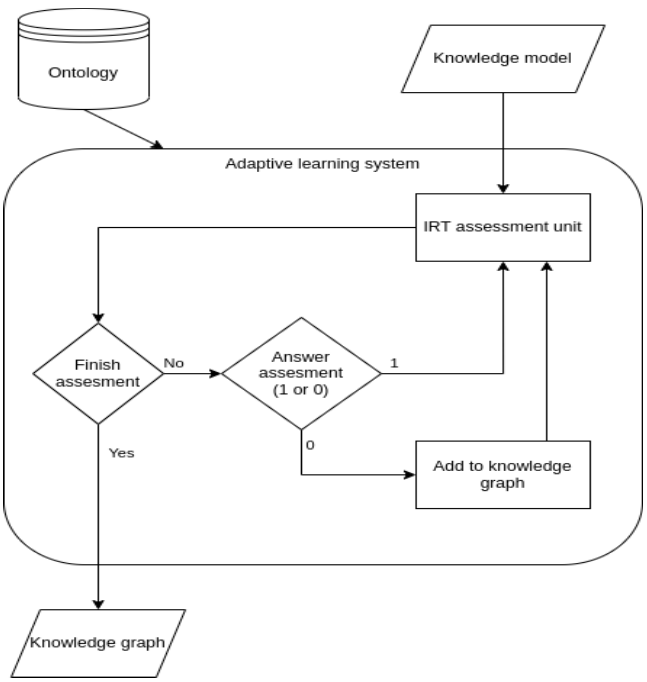

Figure 3: Adaptive Learning System Architecture

The main functionality of the adaptive learning system is finding knowledge gaps learners might have pertaining to a knowledge domain and outputting a knowledge graph.

The adaptive learning system takes an ontology domain and a knowledge model as input. A knowledge model is a set of questions and leaner answers that has been formatted and provided by the AQG. The knowledge model is passed to the IRT assessment unit for processing.

The foundation of the proposed method of finding knowledge gaps uses Item Response Theory (IRT). IRT is based on two core tenets. 1) A combination of factors known as traits, latent traits, or talents can predict or clarify a person's performance on a test question. 2) An Item Characteristic Curve (ICC), which is a progressively increasing function, characterises the relationship between how well examinees do on a test question and the group of attributes that impact their performance. This function shows that as the trait level improves, so does the likelihood of successfully answering an item [10]. Two models of IRT exist. One model deals with dichotomous (two possible responses such as true or false) responses, and the other model deals with polytomous (more than two responses) responses [11]. Since the user of our system will be answering a series of true or false questions, a dichotomous response model will be used. Another reason to choose IRT is that it is already used in Computer Adaptive Testing (CAT) systems, a well-established Automatic Question Generator that adjusts the difficulty of questions for learners to test their true proficiency in a topic. IRT can be used to assess the response (answers) to questions set by an AQG and model the responses as binary, where 1 is correct and 0 is incorrect. A similar method was used by Boyinbode, O. [12] in a web-based application for a personalised e-learning system.

If the learner were to get a question incorrect, the concept related to the question would be added to the knowledge graph, as it is assumed that the leaner does not fully understand the concept. The concept would need to be identified in the ontology domain, which is input into the adaptive learning system. A problem might arise whereby learners answer questions relating to a concept correctly and incorrectly and create inconsistencies and gaps within the knowledge graph. To account for this matter, a correlation factor would need to be considered. The correlation factor would indicate the similarities and relationships between concepts. Which implies that if a learner does not understand concept "A" and concept "B" is closely correlated to concept "A", concept "A" and "B" are added to the knowledge graph. The correlation factor is adapted by Huang, M.J [20]. The knowledge graph, containing the learner's knowledge gaps forms output for the adaptive learning system.

The adaptive learning system does not require user evaluation as it is an intermediary in the whole system which users will not directly interact with. Evaluation of components of the system needs to be done to ensure proper functionality and reliability. The evaluation will inform us whether our approach is accurately detecting a learner's inadequate comprehension of a topic. The core issues of the system that need to be evaluated are; whether the system correctly identifies all the axioms in the ontology; how the IRT algorithm checks the answers to the question; how the IRT algorithm identifies the correct concept(s) that the learner struggles with; and whether the output of the knowledge graph is correct in terms of structure and content. These evaluations could be carried out by either white box testing, such as unit tests, or black box testing, where input is given, and the output is observed.

3.3 NATURAL LANGUAGE GENERATION ALGORITHM

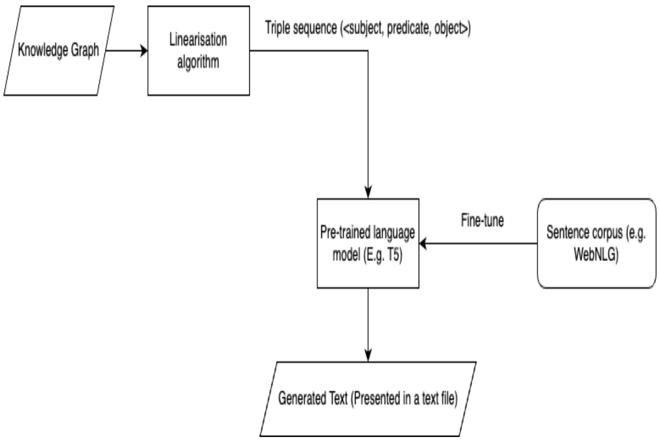

Figure 4: Natural Language Generation System Architecture

Once the user decides to stop answering questions and wants to access the informative document to learn about the gaps in their knowledge, the system will then make use of the logic described here (See Figure 4). The proposed method here is partly inspired Li et al. [1]'s solution for knowledge graph-to-text generation. The knowledge graph containing the content that has been identified as missing from the learner's knowledge from task two is linearized so that a word sequence can be obtained since the pre-trained language model cannot accept the knowledge graph as input. It is to be noted that the amount of detail and relevancy to the content in the output document will come mostly from the knowledge graph. It is much easier to manipulate the knowledge graph so that it can be fed as input to the language model than trying to modify the architecture of the language model to accept the knowledge graph. To prevent the language model from creating invalid facts, it will be fine-tuned on training data obtained from a sentence corpus like WebNLG. To reduce errors due to pronoun ambiguity, positional embeddings as proposed by Wang *et al.* [18] can be added to the linearised word sequence.
To evaluate the performance of this method, the BLEU-4 [2] and ROUGE-L [3] metrics will be used, and the scores obtained will be compared to those of Li *et al.* [1]'s solution. BLEU-4 measures how many words from the machine-generated sentence appear in the human-written one (precision), and ROUGE-L measures how many words in the human-written sentence appear in the machine-generated one (recall). WebNLG is the domain that will be used to get data for training and testing.

3.4 EVALUATION OF THE SYSTEM

We are going to have a series of question-answer pairs to test whether the system can handle different test cases like when a wrong answer is given. This allows us to control the input to better assess the output of the system. After these preliminary tests, user testing will be used with the system to test its usability and get constructive feedback from prospective users. During user evaluation, to determine the expected knowledge gaps, the user will be assessed through a manually set test based on a selected topic whose domain exists in the ontology. The user will then be allowed to use the system, and the output, which is an informative document, will be checked against the manual test to verify if the right knowledge gaps were identified. User testing will be done with different users of different knowledge levels to ensure that the system is usable by a wide range of people.

4 ETHICAL, PROFESSIONAL AND LEGAL ISSUES

This project will need ethics clearance from the UCT ethics board. The system will require personal details like age and name from the user, including their answers when testing. This can be seen as an ethical concern regarding user privacy. Therefore, we will notify the user and request permission to store their data. The users will mostly comprise some select students, each in a different age group and our supervisors. The utilization of publicly available software and datasets will be incorporated in the project. Any beneficial code libraries, associated works, or external contributions will be properly acknowledged and cited to guarantee adherence to copyright and intellectual property regulations. The authors have the copyright over the academic papers for this project, subject to certain rights of University of Cape Town (UCT).

5 RELATED WORK

5.1 COMPUTERISED ADAPTIVE TESTING

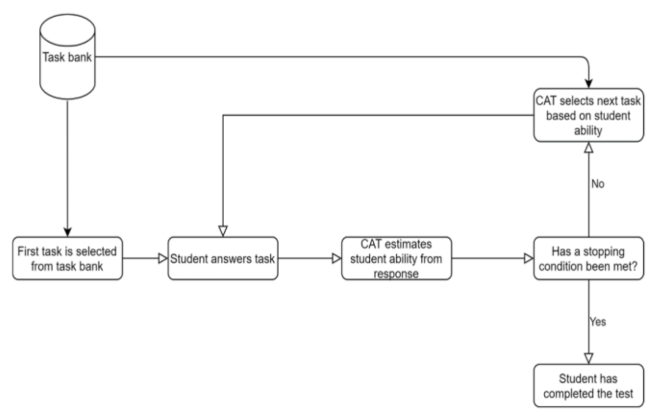

Figure 5: Computerized Adaptive Testing Process Diagram in [7]

Computerised Adaptive Testing (CAT) is an automatic question generation technique. CAT is typically used in one-off tests [8]. However, it will be improved and configured to work on an ongoing basis to provide an updated learner knowledge model for adaptive material generation purposes. CAT works by associating a difficulty level to each potential question using Item Response Theory (IRT) [7]. These questions would then be stored in an item bank and would be selected as a question for the user when the algorithm requires a question matching its difficulty. Each answer provided by the user will result in a different question being asked that matches their knowledge. Thus, each learner will receive different questions, assuming that they do not answer every question exactly the same.

5.2 PERSONALISED ADAPTIVE ENGINE

Boyinbode, O. [12] created a web-based personalised e-learning system that uses an ontology as its knowledge domain. The powerhouse of the e-learning system is the personalised adaptive engine. The personalised adaptive engine oversees supplying individualised learning content based on the learner's model, which is accomplished by combining instruction items to form organised content. It collects information about the learner and learning objects through intermediaries and regularly tests knowledge and abilities. The item response theory is used to evaluate performance [13]. Item response theory is a model-based approach for selecting appropriate learning items based on an analysis of the relationship between a learner's abilities and their responses to the items. It works on the premise that the likelihood of a correct response to an item is determined by personalised and itemised variables, and it uses this information to determine the best learning items for the learner.

5.3 PRE-TRAINED LANGUAGE MODEL

Pre-trained language models are trained on a large dataset for Natural Language Processing (NLP) tasks. This allows the models to capture the general features of the language. They can then just be fine-tuned, for a specific NLP task such as ours, which saves us a considerable amount of time and gives us a better performance from the language model. Li et al. [1] show the power of using pre-trained language models for our task. They propose a relation-biased breadth-first search (RBFS) strategy to linearise the knowledge graph to make it acceptable to the language model. This is an easier way to go about doing this compared to something like Koncel-Kedziorski et al. [9]'s method, which uses a graph transformer to process the knowledge graph. Wang et al. [18] also propose a method for knowledge graph-to-text generation using a pre-trained language model where they show how adding embeddings to the linearized graph can be useful in containing most of the information represented by the knowledge graph.

6 ANTICIPATED OUTCOMES

6.1 SYSTEM

The system comprises three interconnected modules, each containing their own functions. The modules rely on each other to present a complete system capable of delivering a full adaptive learning experience for the user.

The first module is an AQG (Automatic Question Generator), whose main functionality is to generate a set of True or False questions. The AQG has two tasks. The first task is to generate an initial, standardised test for every new user to take. This test is the same for every user and is used to assess learners' raw knowledge about concepts. The second task of the AQG is to generate true or false questions based on the knowledge gaps observed from the previous set of questions, using a knowledge graph as input. The process of repeatedly generating new questions based on the results of previous questions is crucial to accurately identifying all knowledge gaps a learner might have.

The second module is an adaptive learning system capable of identifying knowledge gaps a learner might have about a knowledge domain. The adaptive learning system makes use of a set of questions and answers, called a learner knowledge model, provided by a learner to evaluate whether the learner got a question correct. Once a set of results has been produced, it uses an ontology containing the knowledge domain to identify any knowledge gaps a learner might have. It's assumed that a learner has a knowledge gap when they incorrectly answer multiple questions pertaining to the same concept. The adaptive learning system outputs the learner's knowledge gaps in the form of a knowledge graph for easy processing by other modules.

The third and final module involves using a natural language processor (NLP) to produce documents for the user should they decide to stop answering the system-generated questions. The document involves using a knowledge graph that contains the knowledge gaps of a user and presenting them in a readable human language. The aim of this module is to organise and effectively communicate the knowledge gaps to the learner.

The three modules are organised and communicate with each other in a way that output from one is input to another. The major challenge that might arise is the difficult task of integrating the three modules to create a complete system that runs as expected. Each individual module could run as anticipated; however, once they are integrated with another, the expected functionality might fail. It's important that code structure be maintained and that we ensure high cohesion and low coupling. Extensive testing needs to be done on both the individual modules and the system.

6.2 EXPECTED IMPACT OF THE PROJECT

The main goal of our project is to provide educational resources to learners based on topics that they do not fully understand. With an adaptive learning system, a learner would be assessed by the system, which would automatically generate educational resources to accommodate knowledge gaps. Instead of the learner being provided the same educational materials as the rest of their class in the hope of bettering their understanding of a topic, they are provided personalised resources that consider topics they lack understanding of and by how much (degree of knowledge on that topic).

With a system that acts as an educational tool and can accommodate learners academically, we could see a shift towards more reliance on e-learning in educational institutions. Although e-learning is prominent in tertiary institutions, it is not used that often in primary and secondary educational institutions. This system could change the way teachers teach as it would fill a gap in most educational institutions. The educator is unable to accommodate for each individual learner's learning style and degree of knowledge of the educational content. An adaptive learning system fills in this gap, and educators could see having technology in the learning environment as more of a benefit.

Lastly, the proposed adaptive learning system would provide a better e-learning experience for learners as it personalises educational resources for each learner. The learning benefits of having an e-learning system that can cater to each learner outweigh the benefits of the more commonly used static e-learning systems of today. Furthermore, our system would have the capability of automatically generating educational resources, a functionality that is not prominent in existing adaptive learning systems. This project aims to provide motivation for research into developing a complete adaptive learning system capable of providing a unique experience for each user.

6.3 KEY SUCCESS FACTORS

The key success factors of this project will be based on the aims identified and whether they are achieved:

- The AQG module generates questions that are deemed viable by teachers,
- The adaptive learning module can correctly identify a learner’s knowledge gaps by correctly interacting with the AQG module,
- The system successfully generates an informative document for the learner where they can learn about contents that they do not know, and
- The system improves on aspects of existing adaptive learning systems.

7 PROJECT PLAN

7.1 REQUIRED RESOURCES

The resources required for the project consist of personal computing devices on which the development of the software will take place. A version control system such as GIT will be used to ensure smooth integration of the individual components. No other special software would be required for the successful implementation of the software. The testing phase of the project will require human cooperation, specifically from teachers or lecturers who would have knowledge within the academic field.

7.2 DELIVERABLES

There are multiple deliverables due over the course of the project. The two primary deliverables of the project are a final project paper as well as a final software submission. The other deliverables will be listed below.

- 3 Literature Reviews
- Project Proposal
- Final Paper
- Final Code along with Documentation
- Project Poster
- Project Website

7.3 MILESTONES

Listed below are various milestones that will be reached over the duration of the project. These milestones may also be viewed on the GANTT chart in *Appendix B*, with the yellow diamonds representing project milestones.

- Ethics application completed – *12th May 2023*
- Project preparation completed – *12th May 2023*
- Testing completed (Modules and system) – *16th August 2023*
- Final version of paper submitted – *11th September 2023*
- Code submitted – *15th September 2023*
- Project poster submitted – *9th October 2023*
- Project webpage submitted – *16th October 2023*

7.4 WORK ALLOCATION

The project will be split up equally into three different components. These three components will consist of:

- An Automatic Question Generation Algorithm by *Nervesh Naidoo*
- An algorithm that determines a learner’s knowledge gaps by *Aakief Hassiem*
- An algorithm that creates and renders the adaptive learning materials in natural language by *Keshav Nathoo*

The completion of the other deliverables will be equally collaboratively undertaken by all team members. This includes the creation of the project poster and website.

7.5 RISK ANALYSIS

View *Appendix A*

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APPENDIX A

Risks	Probability	Impact	Consequence	Mitigation	Monitoring	Management
Constantly shifting research aims	Medium	High	Delay in project progression as new objectives must be met for the project to progress. Wasted time due to having to do new research.	Ensuring a common understanding of what is required with the supervisor	Frequent communication with the supervisor to ensure that the project is on the right track	Hold meetings with the supervisor to refocus the goals of the project
Supervisor not always available – Absence of involvement	Low	Medium	The produced system might not meet the requirements of the initial project. Supervisor might not approve.	Frequently engage with the supervisor and schedule regular meetings to discuss progress being made.	Keep track of attendance of team members as well as supervisor to identify any potential problem.	Set up a high-priority meeting with the supervisor, informing them about talking points beforehand. Carry on working on the project while waiting for feedback.
Lack of understanding about the research topic	Medium	Medium	Delays in the project progression as the knowledge required to implement key features might be insufficient.	Ensure that all knowledge points are identified for members to find appropriate learning material.	Keep track of tasks that are taking more time than anticipated. Come up with reasons why and ideas on how to fix it.	Read research papers about the topic that lacks understanding.
Ineffective time management	Medium	High	Delayed project milestones and components which can ultimately delay the entire project	Carefully planning the project schedule as well as holding frequent team meetings to ensure that the project is on schedule	Hold frequent team meetings to discuss progress as well as future objectives relating to the project	Dedicate additional time to delayed objectives to get it back on track so as to not delay the entire project
Code integration issues	Low	High	The individual components of the system would not integrate resulting in an incomplete system that does not achieve the project goals	Clearly identify the inputs and outputs of each component and build each component with this in	Ensure that each team member is creating the individual component with the specified input and	Identify inconsistencies with the version control system and then refactor the code to ensure smooth integration

				mind. Utilize a version control system such as GIT	output in mind	
Withdrawals of project partners	Low	High	An increased workload for the remaining team members with no additional time granted. This may result in an unsatisfactory project	Ensure that each team member understands everyone's individual component	Frequent team meetings to discuss possibilities of a team member leaving	A remaining team member will need to take over the responsibilities of the withdrawing team member

APPENDIX B