Bournemouth University

FACULTY OF SCIENCE & TECHNOLOGY

MSc Data Science and Artificial Intelligence
2025

Adaptive AI Tutor: Personalised Learning and Concept Explanation Using Natural Language Processing (NLP)

by

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Abstract

This project outlines the creation of an intelligent tutoring system that has employed the use of ML and NLP to enable smart education. The study starts with the literature review that presents the recent developments in adaptive learning technologies and NLP in context of education. Data preparation of learners' parameters, grouping, and reinforcement learning was used in this study to tailor the delivered learning material. The techniques of evaluation for supervised classification models include accuracy, number of attributes, precision and recall, F1-scores and BLEU and ROUGE-L. While the system achieved moderate performance, it established a strong foundation for learner adaptation modelling and content personalisation. The text-based evaluation metrics then checked the correctness of semantic maps generated for the predicted and reference content. The study also compares how the integration of cluster analysis and reinforcement learning is useful in improving education; it offered recommendations as follows; deep learning, where NLP needs to be integrated deeper, real-time reinforcement of the model and addition of the model to other areas of education.

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Date: 15 May 2025

Programme: MSc Data Science and Artificial Intelligence

Original Work Declaration

This dissertation and the project that it is based on are my own work, except where stated, in accordance with University regulations.

Signed: Rushikesh Temghare

Name: Rushikesh Temghare

Date: 15 May 2025

Acknowledgments

I would like to sincerely thank Bournemouth University for providing the learning environment and resources that made this project possible. My heartfelt thanks go to my supervisor, Dr. Hari Pandey, for his continuous support, guidance, and honest feedback throughout this project. His insights were extremely valuable, and I'm especially grateful as he also taught me Artificial Intelligence during my first semester, which helped shape my understanding of this field from the very beginning. Lastly, a big thank you to my family and friends for always encouraging me and keeping me motivated along the way.

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1 INTRODUCTION

1.1 Context

Traditional learning approaches often fail to accommodate separate learning paces, styles, and preferences (Humphries and Clark, 2021). With the beginning of Artificial Intelligence (AI), personalised learning has arisen as a ground-breaking approach to enhancing education. Adaptive AI tutors influence Natural Language Processing (NLP) to provide lively, real-time support tailored to each student's needs (Dhananjaya et al., 2024). By analysing student responses, identifying delusions, and regulating content accordingly, NLP-powered tutors offer a more appealing and actual learning experience (Shravya, Nair, and Kadur, 2019).

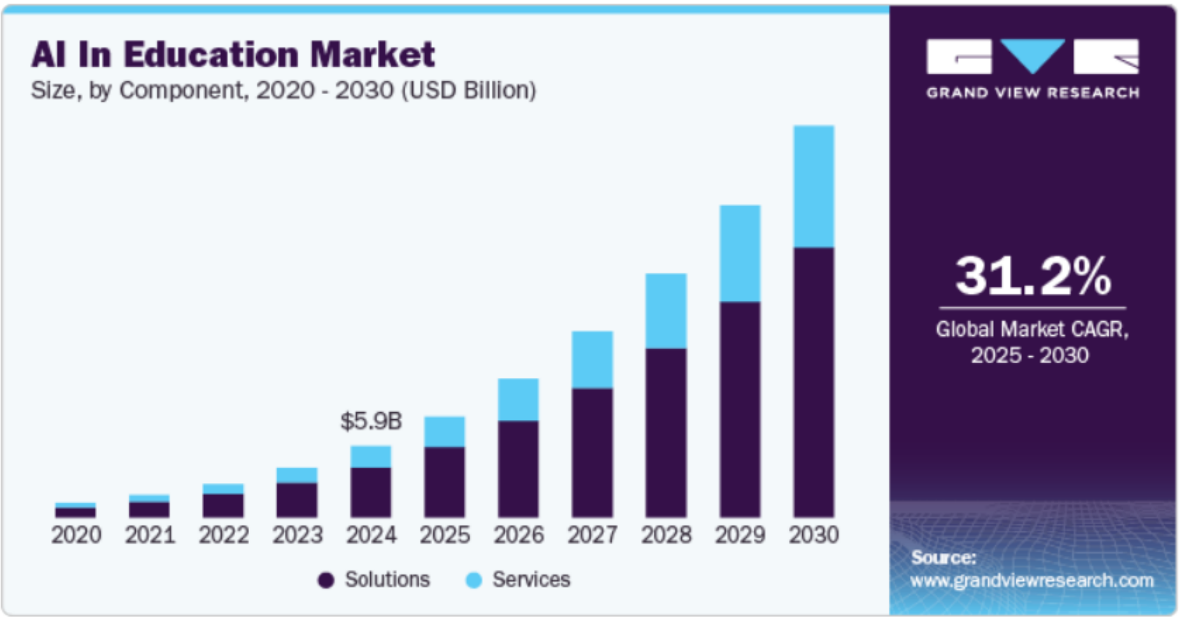

Figure 1: AI in Education Market (Source: www.grandviewresearch.com)

Figure 1, NLP enables these tutors to comprehend natural language queries, produce meaningful clarifications, and adapt to diverse cognitive levels. Through methods such as sentiment analysis, entity recognition, and context-aware response generation, AI tutors enhance student understanding. Additionally, strengthening learning allows the system to recover its accuracy over time by analysing student feedback and performance trends (Troussas et al., 2023).

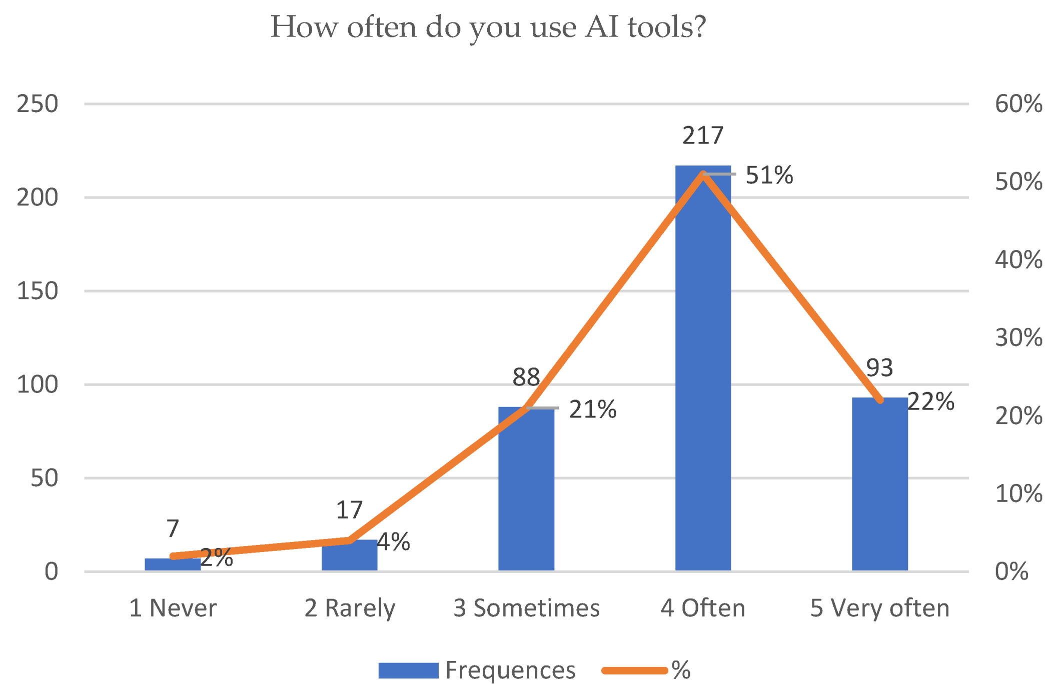

Figure 2: Usage of AI tools (Fošner, 2024)

The implementation of adaptive AI tutors has demonstrated improvements in learning efficiency, knowledge holding, and student engagement. Studies indicate that personalised AI tutors significantly outperform static, rule-based educational systems. The integration of NLP in education also reduces the dependency on human instructors while maintaining high-quality learning experiences.

1.2 Motivation and Rationale

The rationale for this project lies in the need to address the limitations of traditional educational tools, which often do not meet the diverse needs of learners. An AI-powered adaptive tutor, utilising NLP, and reinforcement learning, can provide a dynamic and personalised learning experience, offering tailored support in real-time. This approach not only fosters student engagement but also helps in improving comprehension and critical thinking. The use of AI enables continuous assessment and feedback, empowering students to learn at their own pace, and contributing to enhanced educational outcomes (Swargiary, 2024).

The motivation behind developing an AI-powered adaptive tutor stems from the increasing need to enhance personalised learning in educational environments. Traditional teaching methods often fail to cater to individual student needs, leading to disengagement and poor academic performance. By leveraging Natural Language Processing (NLP) and adaptive algorithms, an AI tutor can provide real-time, personalised explanations that adapt to each student's learning pace and style. This technology has the potential to bridge gaps in understanding, boost student engagement, and significantly improve learning outcomes, aligning with the growing demand for personalised, scalable educational tools (Ellikkal and Rajamohan, 2024).

1.3 Problem definition

Students frequently face challenges in grasping complex concepts due to the limitations of traditional educational tools, which often adopt a one-size-fits-all approach (Yang, S. *et al.* 2019). These tools, such as textbooks and lectures, may not cater to the diverse learning needs, preferences, and paces of individual students. As a result, students who struggle with certain topics may find it difficult to keep up, leading to disengagement and reduced academic performance (Schnitzler, K., Holzberger, D. and Seidel, T. 2021). Moreover, the lack of personalised feedback and adaptive learning resources exacerbates the issue, as students do not receive the necessary support to understand challenging material at their own pace. This gap in effective learning strategies can result in poor retention of information and hinder the development of critical thinking skills (Ramos, K.R. 2024). Consequently, it becomes crucial to explore and implement personalised learning approaches that address students' unique learning styles, enabling them to overcome these obstacles and achieve better learning outcomes (Rekha et al., 2024).

1.4 Aims and Objectives

1.4.1 Aim

The aim of this project is to develop an AI-powered adaptive tutor that provides personalised educational support and real-time explanations, leveraging NLP to enhance learner comprehension, engagement, and overall learning effectiveness.

This project has following objectives:

1.4.2 Project Objectives

1. To conduct a comprehensive literature review to explore existing adaptive learning technologies, the role of NLP in education, and the design of personalised AI tutoring systems. The review sets a theoretical foundation of this project.
2. To design and implement adaptive algorithms, including reinforcement learning for content adjustment and clustering techniques for learner profiling, to create a personalised and dynamic AI-powered tutoring system.
3. To evaluate performance using predefined metrics such as accuracy, precision, recall, F1-score, BLEU, and ROUGE, focusing on its ability to provide accurate responses and adapt to diverse learning profiles through simulations.
4. Summarise the findings, draw conclusions, and propose future research directions for enhancing adaptive learning technologies and expanding their applications to diverse educational contexts.

1.5 Research Questions

RQ1. How effective is an AI tutor, using Natural Language Processing (NLP), in providing personalised learning experiences to students with varying knowledge levels?
RQ2. What is the impact of an adaptive AI tutor, utilising reinforcement learning algorithms, on student understanding, comprehension, and engagement?
RQ3. What is the accuracy of the AI tutor in answering questions using NLP techniques, and how does this accuracy influence learning outcomes?

1.6 Thesis Organisation

This research is organised into six chapters where each chapter explains one of the main aspects involved in developing an AI Powered Adaptive Tutoring System. Chapter 1 provides the motivation, aims, and the role of NLP and reinforcement learning in this study. Chapter 2 draws a literature of adaptive leaning, NLP in education and AI design. Chapter 3 describes the methodology that involved learner profiling and model evaluation. In the Chapter 4, as regards the implementation, tools and technologies employed are discussed. Chapter 5 reports results of adaptive system performance. Chapter 6 end of the study; it summarises the findings, defines limitations, and suggests directions for future research in adaptive educational technologies.

2 LITERATURE REVIEW

This chapter presents a literature review about AI-driven adaptive learning systems. It points to the confined set of a typical e-learning system in that it takes a “one size fits all” attitude so sending it to all the students the same content regardless of their differences in their characteristics, learning styles, or cognitive abilities. This trend that has been criticised for the poor outcome in learning and student disinterest. Compared, adaptive learning systems apply machine learning (ML) and artificial intelligence (AI) to modulate educational experiences: the content delivery is formulated to its concrete needs and goals (El-Sabagh, 2021) and (Beldagli and Adiguzel, 2010). This chapter supports the Objective 1 by discussing the areas of AI-driven adaptive learning by focusing on how adaptive AI tutors use Natural Language Processing to offer students personalised learning and clarification of concepts.

2.1 Adaptive Learning and AI-Powered Personalisation

An AI-driven strategy called personalised learning (PL) aims to adjust course material to each student's requirements, preferences, and performance. It provides tailored learning routes by using machine learning algorithms to assess students' learning preferences, areas of strength, and areas of weakness (El-Sabagh, 2021). In order to guarantee that students obtain information appropriate for their cognitive capacities and rate of advancement, PL creates an interactive, self-paced learning environment (Ingkavara et al., 2022).

Recommendation algorithms are used by AI-powered PL systems to monitor students' progress and provide pertinent materials to improve comprehension. Additionally, these systems use natural language processing (NLP) to provide real-time feedback and intelligent teaching (Gkintoni, Halkiopoulos and Antonopoulou, 2022). Research shows that by matching educational materials to students' needs, PL increases learner engagement and retention (Ryan and Poole, 2019).

The use of AI approaches to modify learning materials, paths, and assessments in response to a learner's performance and development is known as adaptive learning. In order to dynamically modify instructional materials, these systems use machine learning algorithms to evaluate student interactions, assessment outcomes, and engagement levels (Ennouamani and Mahani, 2017). Adaptive systems may recognise strengths and weaknesses by continually learning from data, and they can then suggest tailored learning routes that improve understanding and retention.

Learner data is gathered, examined, and utilised to improve learning techniques in the "closed-loop" process that forms the core architecture of adaptive learning systems (Wang et al., 2023). By offering real-time feedback, flexible scheduling, and individualised material delivery, artificial intelligence (AI) improves adaptive learning and the learning process as a whole (Moreno-Guerrero et al., 2020). By incorporating natural language processing (NLP) into these systems, customisation is further enhanced and students may receive engaging, human-like answers to their questions.

2.2 Role of NLP in Adaptive Learning

Because it facilitates dialogue and intelligent content creation, natural language processing, or NLP, is essential to adaptive AI teachers. With the use of natural language processing (NLP), the system can comprehend, interpret, and reply to students' questions while offering answers that make sense. NLP-based AI instructors may measure student attention and modify explanations based on sentiment analysis and pattern recognition (Tapalova and Zhiyenbayeva, 2022).

NLP can produce individualised feedback systems and adaptive tests by analysing enormous volumes of text data. NLP-enabled AI instructors are able to examine student-generated replies, identify misunderstandings, and provide focused explanations. This interaction creates a more dynamic and interesting learning environment by simulating human teaching (Park et al., 2024).

An AI-based evaluation technique called adaptive assessment (AA) dynamically modifies the level of assessment difficulty according on a learner's performance. In contrast to conventional standardised testing, AA uses machine learning models and item response theory (IRT) to customise assessments (Chang, Li and Huang, 2022). In order to improve assessment accuracy and learning outcomes, these algorithms adjust question difficulty based on students' replies in real time (Abhirami and Kavitha Devi, 2022).

According to research, by reducing test anxiety and offering customised feedback, AA helps provide a more equitable assessment of students' knowledge (Hoffmann, 2022). Real-time insights into students' progress are provided by AI-based assessment tools like intelligent quizzes and formative feedback systems, which enable teachers to spot knowledge gaps and modify their teaching methods accordingly (Anoir, Khaldi and Erradi, 2024). But PL implementation necessitates large datasets and sophisticated computing power, which raises privacy and data security issues (Cope and Kalantzis, 2023).

2.3 Machine Learning and Learners Module

Because it makes it possible to create prediction models that evaluate student behaviour and enhance teaching methods, machine learning (ML) is essential to adaptive learning. Large datasets are analysed by ML algorithms to find trends in student performance, which enables the system to dynamically modify instructional materials (Rabelo et al., 2024). Cognitive skills, knowledge levels, and learning preferences are all included in learner models built with machine learning (ML), which serve as the foundation for providing tailored material.

ML-based customisation strategies are used by adaptive AI instructors to modify the difficulty of the material and suggest additional resources. By ensuring that training is tailored to each learner's pace and comprehension, these methods increase motivation and engagement (Pontual Falcão et al., 2018).

2.4 Historical Evolution of AI in E-Learning

Early AI-based tutoring systems, the development of intelligent learning environments, and contemporary AI-driven educational platforms are the three stages in the growth of AI in e-learning.

Table 1: Historical Evolution of AI

Phase	Description	Key Developments
Early AI-based Tutoring Systems (1980s-1990s)	AI systems focused on rule-based tutoring, providing limited adaptive instruction.	Development of Intelligent Tutoring Systems (ITS) such as SCHOLAR and SOPHIE (Guo et al., 2021).
Intelligent Learning Environments (2000s-2010s)	AI incorporated advanced analytics, improving adaptivity in education.	Introduction of NLP and data-driven personalisation in learning platforms (Yu and Chauhan, 2024).
Modern AI-driven Educational Platforms (2010s-Present)	AI applications integrate deep learning and big data analytics for personalised education.	Implementation of AI-powered chatbots, recommendation systems, and automated grading (Vashishth et al., 2024).

The development of AI throughout time demonstrates how it is increasingly being used to improve teaching strategies. In order to create intelligent, scalable, and data-driven e-learning ecosystems, the current emphasis is on deep learning-based models that improve PL and AA (Ibisu, 2024).

2.5 Classification and Critical Analysis

Table 2 enumerates a tendering classification of AI technologies available in e-learning which describes the key categories, descriptions, the technology used, the benefits offered, and reference to (illustrate) the roles of AI which has been evolving over time, more so in adaptive learning; NLP integration; learner modelling; and history of AI in education.

Table 2: Classification of AI Technologies in E-Learning

Section in the chapter	Category	Description	Key Technologies/Methods	Benefits	References
2.1	Adaptive Learning and AI-Powered Personalisation	Personalised learning through adaptive algorithms that tailor content to individual needs.	Machine Learning, Recommendation Algorithms, NLP	Self-paced learning, improved retention, enhanced engagement	(El-Sabagh, 2021), (Ingkavara et al., 2022), (Gkintoni, Halkiopoulos and Antonopoulou, 2022), (Ryan and Poole, 2019), (Ennouamani and Mahani, 2017), (Wang et al., 2023), (Moreno-Guerrero et al., 2020),
2.2	Role of NLP in Adaptive Learning	NLP enables intelligent communication, feedback, and assessments.	NLP, Sentiment Analysis, Pattern Recognition, Adaptive Assessment, Item Response Theory (IRT)	Intelligent feedback, dynamic assessments, personalised explanations	(Tapalova and Zhiyenbayeva, 2022), (Park et al., 2024), (Chang, Li and Huang, 2022), (Abhirami and Kavitha Devi, 2022),

					(Hoffmann, 2022), (Anoir, Khaldi and Erradi, 2024), (Cope and Kalantzis, 2023).
2.3	Machine Learning and Learners	Module ML supports modelling learner behaviour and adapting content.	ML Algorithms, Predictive Analytics, Learner Modelling	Tailored instruction, enhanced motivation, real-time adjustments	(Rabelo et al., 2024), (Pontual Falcão et al., 2018).
2.4	Historical Evolution of AI in E-Learning.	Timeline of AI integration into educational systems	Rule-Based Systems, NLP, Deep Learning, Big Data Analytics	Improved adaptability, automation, personalised platforms	(Guo et al., 2021), (Yu and Chauhan, 2024), (Vashishth et al., 2024), (Ibisu, 2024).

2.6 Gaps

Even though there is abundant material about AI driven adaptive learning methods, the literature does identify several gaps. First, there is not much written about the ethical implications that the collection and processing of sensitive learner data gives rise to data privacy and security concerns. Besides, even though applications of NLP and ML are well explored, little attention is paid to the real-world challenges of implementation, such as scalability or system interoperability and resistance of learners. Literature does not measure long-term learning outcomes and equity impacts across various populations of learners as well. In addition, comparative analysis regarding the efficacy of different AI models in different educational settings has been underdeveloped.

2.7 Summary of Chapter

This chapter investigates how AI-powered adaptive learning might improve the customisation of e-learning. While AI-powered systems employ machine learning (ML) and natural language processing (NLP) to customise learning experiences, conventional e-learning does not offer this capability. Personalised evaluations and real-time feedback are provided via adaptive learning, which dynamically modifies the curriculum according to student performance. NLP makes it possible for AI teachers to comprehend and intelligently react to questions, which improves engagement. Along with discussing AI's advantages—like higher engagement—and drawbacks—like data privacy issues—the chapter also charts the development of AI in education. Enhancing learner modelling, NLP interactions, and the ethical use of AI should be the main goals of future research.

3 METHODOLOGY AND PLANNING

The text presents a 16-week development schedule for an AI adaptive tutor which adopts Agile practices combined with Scrum and Kanban structures. The project starts with research that leads to system design for model development through the implementation of NLP alongside reinforcement learning techniques for specific content delivery methods. The developer process involves multiple timeframes for testing integrating learner profiling and delivering content based on accuracy and F1-score, BLEU, and ROUGE metrics. The project implements Python together with TensorFlow and Hugging Face in addition to Trello as its primary tools. Weekly supervision ensures steady progress. Several risk management approaches exist to solve performance and time-related and technical issues. Intelligent tutoring along with personalised education methods function as the primary objective of this project to improve student learning results.

3.1 Planning

The 16-week project follows two weeks of research on adaptive learning, educational NLP, and AI tutor technologies. Weeks 3–4 concerns itself with the design of system architecture and choice of algorithm. Weeks 5-7 see development which incorporates reinforcement learning to deliver adaptive content and NLP for interactive responses. During weeks 8–9, learner profiling and content clustering are performed with the help of machine learning. The system evaluation and testing are performed in Weeks 10–12 by some metrics: accuracy, F1-score, BLEU, and ROUGE. Weeks 13–14 are covered by simulations of users, who evaluate personalisation and learning impact. Week 15 is for final reporting and Week 16 is for feedback integration and future planning.

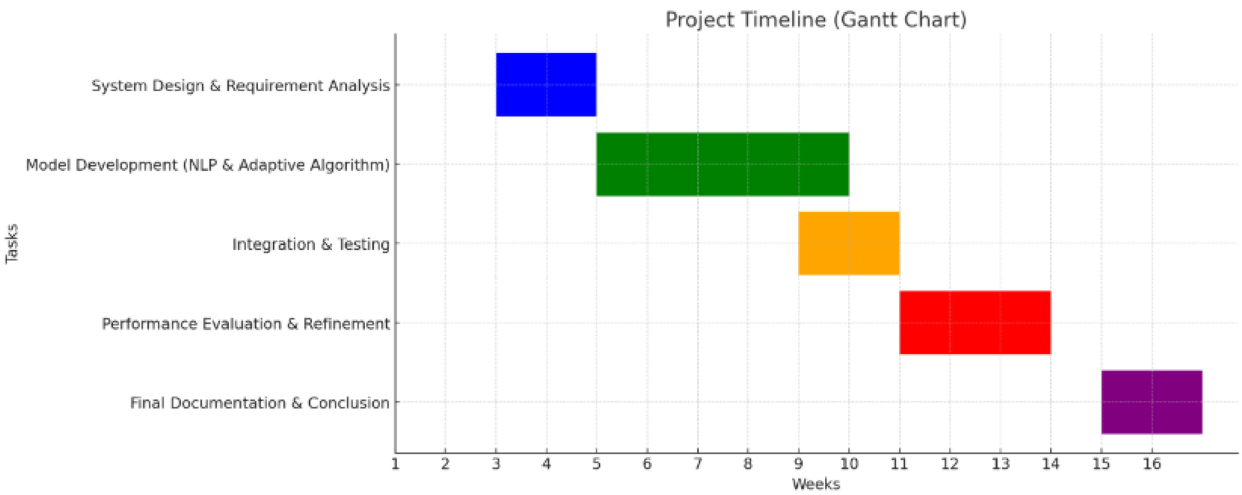

Figure 3: Gantt Chart

3.2 Methodology

Building an AI-powered adaptive tutor needs a well-ordered methodology which delivers both competent implementation and proper assessment. An Agile methodology will direct this complex project that requires multiple iterations. The agile approach fits software-based AI initiatives because it enables frequent development enhancements and handles obstacles through flexible solutions and provides ongoing input-driven system upgrades. The project's methodology will execute an incremental development cycle through which Scrum together with Kanban elements will help monitor steady progression.

3.2.1 Agile Methodology Justification

Agile represents the best choice because it enables essential continuous assessments and adjustments needed for designing AI systems. Agile implementation allows multiple testing cycles and optimisation work in NLP and reinforcement learning models by providing regular feedback from supervisor and simulated user engagements. Necessary adjustments based on performance evaluations can be performed through this iterative approach to ensure the system follows learning patterns of diverse students.

Figure 4: Agile Workflow for AI Tutor Development (Source: Self)

3.2.2 Scrum and Kanban Elements

3.2.2.1 Scrum Elements

The project will execute through multiple two-week sprints under the Scrum framework to handle separate tasks before performing reviews. The development cycle under sprint planning begins by setting goals before moving into the stages of creation testing and sprint inspection.

3.2.2.2 Kanban Elements

The system will use a digital or physical Kanban board to show progress between backlog and in progress and review and completed stages. Transparency along with workflow efficiency tracking becomes possible through this system implementation.

3.3 Dataset Description

The dataset at GeminiLight/awesome-ai-llm4education is a curation of scholarly papers on the topic of AI and LLM4education in teaching and learning. It covers a broad spectrum of topics including personalised tutoring system, adaptive learning strategies, an automated tool for assessment and content generation methods. Different pieces of data in the dataset have comprehensive metadata including the name of the paper, authors, publication venue, year, and brief summary which makes it possible for researchers and practitioners to explore AI-generated educational technologies and emerging trends. This resource acts as an important reference for people interested in AI and education intersection.

Dataset-Description:

https://github.com/GeminiLight/awesome-ai-llm4education/blob/main/data/papers.csv

3.4 Tools and Technologies

- **Programming Languages:** Python (for NLP and machine learning development)
- **Frameworks & Libraries:** TensorFlow, PyTorch, Hugging Face Transformers for NLP
- **Data Management:** Pandas, NumPy, Scikit-learn
- **Project Management:** Trello (Kanban board), JIRA (Scrum management)
- **Evaluation Metrics:** Accuracy, Precision, Recall, F1-score, BLEU, ROUGE

3.5 Selected Approaches for Developing an Intelligent Tutoring System

The project makes use of Clustering, and Reinforcement learning (RL) and Supervised machine learning for developing a dynamic and adaptive tutoring system. Learners are profiled and stringBuffer is scaled using numerical features for KMeans clustering allowing individualised instruction. A custom RL environment with a use of the Deep Q-Networks (DQN) dynamically modifies content recommendations according to learner states. Supervised machine learning models, such as Random Forest, Logistic Regression, and Gradient Boosting, are being used for the classification task and the evaluation criteria, would be the metric such as accuracy, F1-score etc. BLEU and ROUGE-L are tools for evaluating text similarity in content quality. These approaches are chosen due to their robustness, flexibility as well as their track record of successful delivery on applications such as personalisation, decision-making and language-based educational applications.

3.6 Risk Management and Contingency Planning

- **Model Performance Issues:** Multiple iterations and testing phases will be conducted to fine-tune AI models.
- **Time Constraints:** Strict adherence to sprint cycles will ensure timely progress.
- **Technical Challenges:** Seeking guidance from research papers and open-source communities will help address unforeseen technical hurdles.

By utilising Agile methodology with Scrum and Kanban elements, this project will ensure a structured yet flexible approach to developing an AI-powered adaptive tutor. With an iterative development cycle and continuous feedback integration, the final system will be optimised for personalised learning, enhancing student comprehension and engagement.

4 IMPLEMENTATION AND EXPERIMENTATION

This chapter focuses on designing, developing, and testing of an ITS by incorporating machine learning and NLP. It starts with the general examination of the dataset to get first insights about the structure and quality of the data in the data exploration phase, then try to find relevant papers for the literature review. The chapter then provides the notion of developing an adaptable tutoring system with the help of clustering and revenue learning. Finally, it addresses the specific case of classification problems to be solved in supervised learning, its performance evaluation and text-based analysis for content similarity; also stressed is applicability of the proposed ITS framework for personal education.

4.1 Exploratory Data Analysis

The raw data comprises of 174 research paper entries in which these papers have 10 attributes, both categorical and numeric. The info () function shows that nearly all the fields are stereo typed with the id column integer type, while the code is not present altogether and the link has one NaN value. Indeed, there is no missing values in the title, category, authors or is_llm_related fields, meaning the dataset is prepared in a relatively hygienically as we analyse it.

```
[3]: # Display basic information
print("Dataset Info:\n")
data.info()
```

```
Dataset Info:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 174 entries, 0 to 173
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   group           174 non-null    object 
 1   category        174 non-null    object 
 2   publisher       174 non-null    object 
 3   year            174 non-null    int64  
 4   type            174 non-null    object 
 5   is_llm_related  174 non-null    int64  
 6   title           174 non-null    object 
 7   link            173 non-null    object 
 8   authors         174 non-null    object 
 9   code            0 non-null      float64
dtypes: float64(1), int64(2), object(7)
memory usage: 13.7+ KB
```

```
[4]: # Display summary statistics
print("\nSummary Statistics:\n")
print(data.describe(include='all'))
```

```
Summary Statistics:

             group           category publisher         year        type  \
count          174                174       174   174.000000         174   
unique           7                 21        39          NaN           4   
top     Assessment  Knowledge Tracing     arXiv          NaN  conference   
freq            75                 36        37          NaN         115   
mean           NaN                NaN       NaN  2022.304598         NaN   
std            NaN                NaN       NaN     2.947377         NaN   
min            NaN                NaN       NaN  2001.000000         NaN   
25%            NaN                NaN       NaN  2022.000000         NaN   
50%            NaN                NaN       NaN  2023.000000         NaN   
75%            NaN                NaN       NaN  2024.000000         NaN   
max            NaN                NaN       NaN  2025.000000         NaN   

        is_llm_related                                              title  \
count       174.000000                                                174   
unique             NaN                                                172   
top                NaN  LLM-powered Multi-agent Framework for Goal-ori...   
freq               NaN                                                  2   
mean          0.356322                                                NaN   
std           0.480294                                                NaN   
min           0.000000                                                NaN   
25%           0.000000                                                NaN   
50%           0.000000                                                NaN   
75%           1.000000                                                NaN   
max           1.000000                                                NaN   
```

Figure 3: Summary Statistics and Dataset Information

Figure 5 presents, the use of descriptive statistics and nunique() provide information about the diverse entries; 21, 39 and 172 concerning categories, publishers, and titles respectively. The is_llm_related column only has BOOLEAN values indicating whether each of the papers discussed in the dataset belongs to the large language models category or not.

```
[5]: # Check for missing values
     print("\nMissing Values:\n")
     print(data.isnull().sum())
```

```
Missing Values:

group             0
category          0
publisher         0
year              0
type              0
is_llm_related    0
title             0
link              1
authors           0
code            174
dtype: int64
```

```
[6]: # Unique values in each column
     print("\nUnique Values per Column:\n")
     print(data.nunique())
```

```
Unique Values per Column:

group             7
category         21
publisher        39
year             13
type              4
is_llm_related    2
title           172
link            169
authors         171
code              0
dtype: int64
```

Figure 4: Missing and Unique Values

Descriptions about the group, category, publisher, and type categorical variables were made through count plots to distinguish the distribution of research themes. The distribution by year shows the papers' trends over the years, whereas is_llm_related displays the measures of the papers about the LLM involvement.

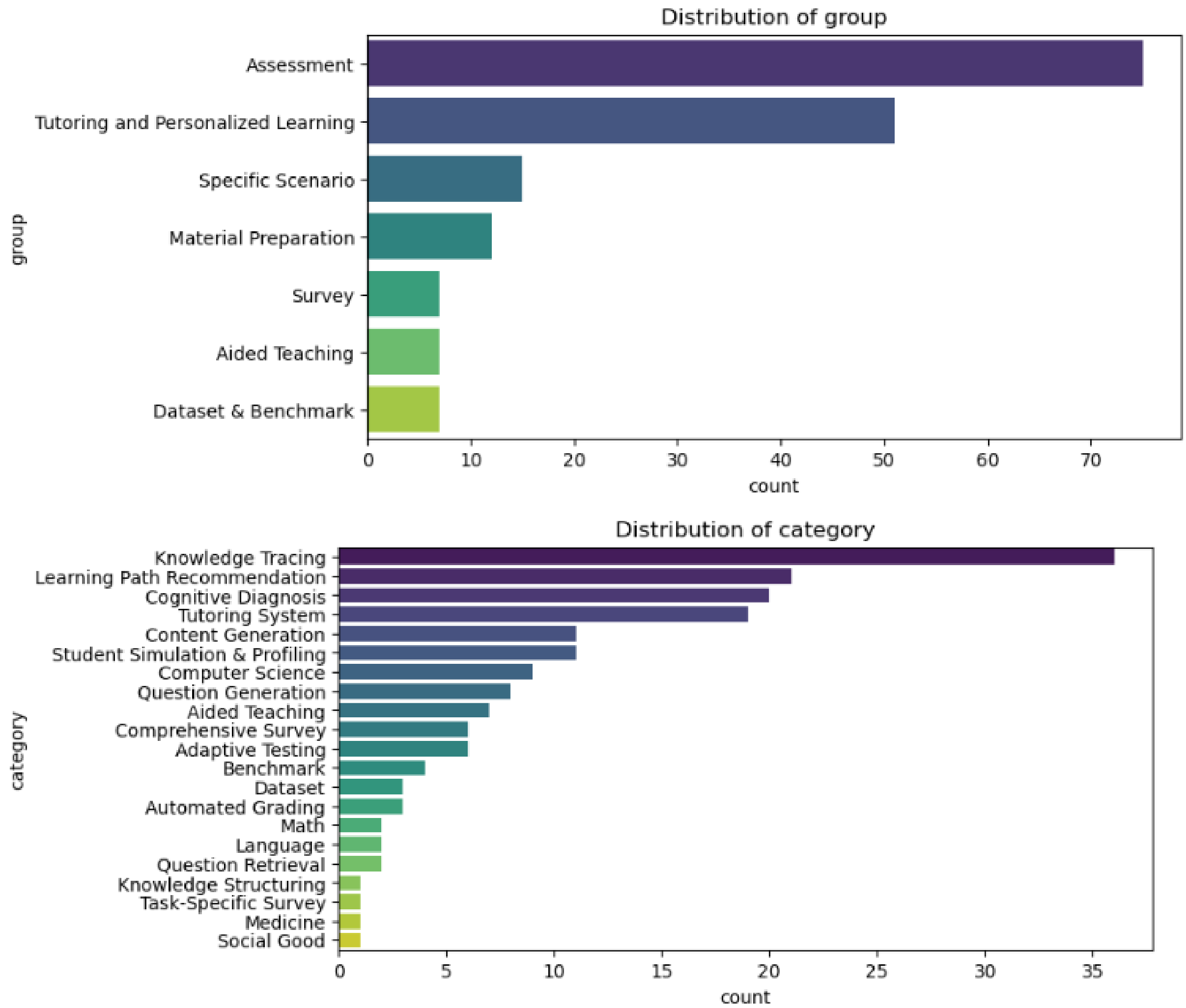

Figure 5: Bar Graphs

Figure 7 presents a bar chart was generated where top 10 publishers are represented to analyse how active they were during the previous period. Figure 11 presents, WordClouds of the title and authors were created where one obtained the understanding of most recurrent terms while the latter helped to identify most active authors in the dataset. In summary, the EDA part is useful for further pre-processing, clustering, or classifying a dataset.

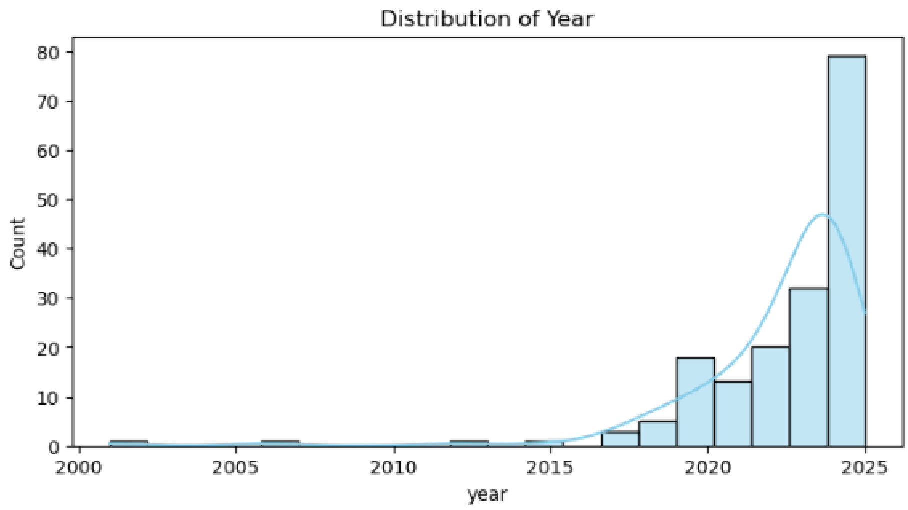

Figure 6: Histogram Plot

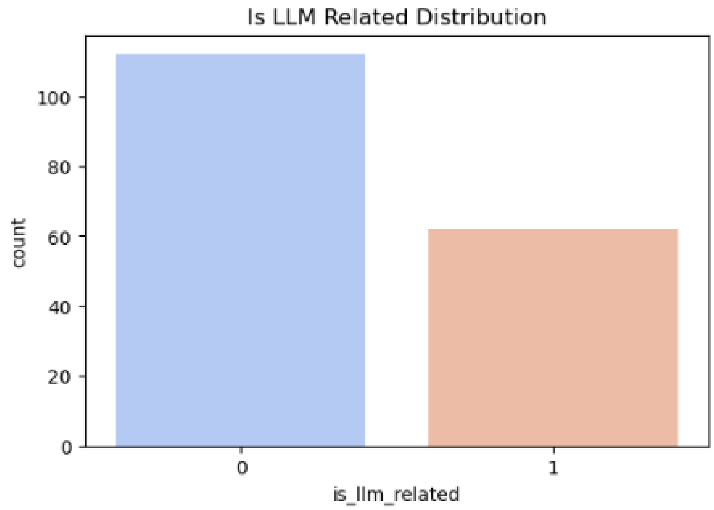

Figure 7: Count Plot

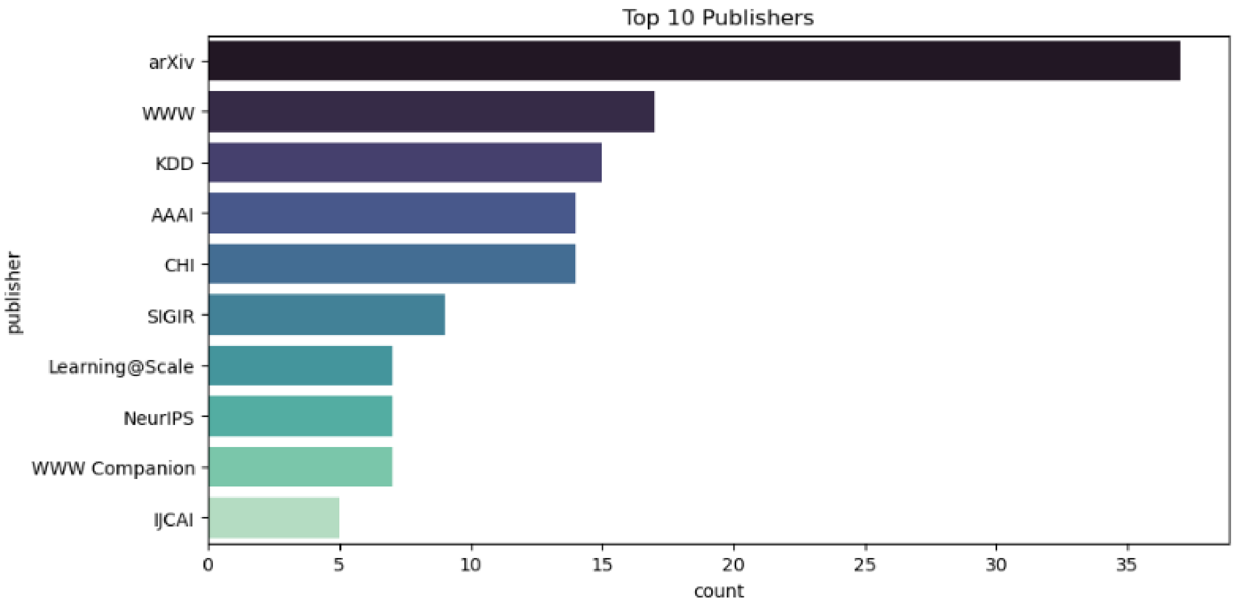

Figure 8: Top 10 Publishers


```
# WordCloud for 'authors'
plot_wordcloud('authors', 'WordCloud for Authors')
```

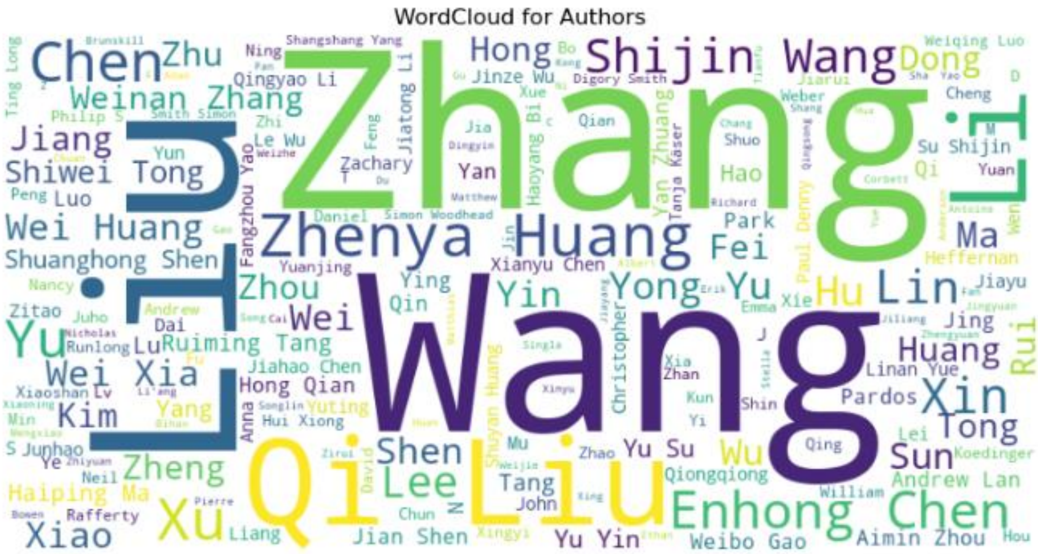

Figure 9: Word Cloud

4.2 Filtered Literature Review Summary

Figure 12 and 13 shows how to obtain the papers related to adaptive-learning, AI-tutoring, personalised-learning, NLP and reinforcement learning, keyword filtering methodology was used. One hundred and thirty-four papers altogether were inspected, of which 17 were closely connected with the Ideas about the project. There is total 6 different themes covered in these papers and 16 of them were published in last five years, which also prove increasing role of intelligent tutoring and adaptive systems.

```
[17]: # Filter relevant papers based on keywords
keywords = ["adaptive learning", "AI tutor", "natural language processing", "personalized learning", "reinforcement learning"]
```

```
[18]: def filter_relevant_papers(row):
          title_match = any(keyword.lower() in row['title'].lower() for keyword in keywords)
          category_match = any(keyword.lower() in row['category'].lower() for keyword in keywords)
          return title_match or category_match
```

```
[19]: # Apply the filter
df_relevant = data[data.apply(filter_relevant_papers, axis=1)]
```

```
[20]: # Display relevant records
print("Relevant Papers:")
print(df_relevant[['title', 'authors', 'year', 'link', 'category', 'is_llm_related']])
```

```
Relevant Papers:
                                                 title  \
1    Reinforcement Learning for Education: Opportun...
8    An Interaction Design for Machine Teaching to ...
11   Empowering Personalized Learning through a Con...
20   How to Build an AI Tutor that Can Adapt to Any...
26   Constraint Sampling Reinforcement Learning: In...
29   Reinforcement Learning for the Adaptive Schedu...
30   Graph Enhanced Hierarchical Reinforcement Lear...
31   Exploiting Cognitive Structure for Adaptive Le...
33   Privileged Knowledge State Distillation for Re...
35   The Effects of Adaptive Learning in a Massive ...
36       Automatic Interpretable Personalized Learning
40   Deep Reinforcement Learning for Adaptive Learn...
45   Learning Path Recommendation Based on Knowledg...
46   Doubly constrained offline reinforcement learn...
119  Enhancing Deep Knowledge Tracing via Diffusion...
159  LLM-Powered AI Tutors with Personas for d/Deaf...
168  PTADisc: A Cross-Course Dataset Supporting Per...

                                               authors  year  \
1    Adish Singla, Anna N. Rafferty, Goran Radanovi...  2021
8       Daniel Weitekamp, Erik Harpstead, K. Koedinger  2020
11   Minju Park, Sojung Kim, Seunghyun Lee, Soonwoo...  2024
20                                         Chenxi Dong  2023
26   Tong Mu, Georgios Theocharous, David Arbour, E...  2022
29   A. Singla, Anna N. Rafferty, Goran Radanovic, ...  2020
30   Qingyao Li, Wei Xia, Li'ang Yin, Jian Shen, Re...  2023
31   Qi Liu, Shiwei Tong, Chuanren Liu, Hongke Zhao...  2019
33   Qingyao Li, Wei Xia, Li'ang Yin, Jiarui Jin, Y...  2024
35   Y. Rosen, I. Rushkin, Rob Rubin, Liberty Munso...  2018
36   Ethan Prihar, Aaron Haim, Adam Sales, Neil Hef...  2022
```

Figure 10: Part 1 of Filtered LR

Among the 17 papers, three of them are labelled under Large Language Models (LLMs), which indicates that newer existing NLP milestones are used in the context of education. This subset of data has been saved in a new csv file known as filtered_literature_review to assist in a more vigorous and relevant analysis to fit the objectives of the project. It also makes it possible to get a view of how thematic research is evolving by object and year grouping them.

```
[21]: # Summarize findings by category and year
summary = df_relevant.groupby(['category', 'year']).size().reset_index(name='count')
print("\nSummary by Category and Year:")
print(summary)
```

```
Summary by Category and Year:
                        category  year  count
0           Comprehensive Survey  2021      1
1                        Dataset  2023      1
2              Knowledge Tracing  2024      1
3   Learning Path Recommendation  2018      1
4   Learning Path Recommendation  2019      2
5   Learning Path Recommendation  2020      2
6   Learning Path Recommendation  2022      2
7   Learning Path Recommendation  2023      1
8   Learning Path Recommendation  2024      2
9                    Social Good  2024      1
10               Tutoring System  2020      1
11               Tutoring System  2023      1
12               Tutoring System  2024      1
```

```
[22]: # Export the filtered dataset for detailed review
df_relevant.to_csv('filtered_literature_review.csv', index=False)
```

```
[23]: # Extract key insights
insights = {
    'Total Papers': len(df_relevant),
    'LLM Related Papers': df_relevant['is_llm_related'].sum(),
    'Unique Categories': df_relevant['category'].nunique(),
    'Recent Publications (Last 5 Years)': len(df_relevant[df_relevant['year'] >= 2019])
}
```

```
[24]: print("\nKey Insights:")
for key, value in insights.items():
    print(f"{key}: {value}")
```

```
Key Insights:
Total Papers: 17
LLM Related Papers: 3
Unique Categories: 6
Recent Publications (Last 5 Years): 16
```

Figure 11: Part 2 of Filtered LR

4.3 Adaptive Tutoring System: Pre-processing, Clustering & RL Overview

Figure 14, 15 and 16 describes the missing values that are missing from the dataset, so they must be filled Moreover, the group, category and publisher values are categorical in nature and they have to be encoded. Some of the link values were filled as ‘No Link’ and the extra column code was not utilised. All categorical data were encoded as labels, whereas the quantitative data that included year and is_llm_related were scaled by StandardScaler.

```
[28]: # Preprocessing: Handle missing values
      data.fillna({'link': 'No Link'}, inplace=True)

      # Drop the 'code' column only if it exists (avoids KeyError)
      data.drop(columns=['code'], inplace=True, errors='ignore')

      # Encode categorical variables
      label_encoders = {}
```

```
[29]: # Preprocessing: Handle missing values
      data['link'].fillna("No Link", inplace=True)
```

```
[30]: # Ensure 'code' column exists before dropping
      if 'code' in data.columns:
          data.drop(columns=['code'], inplace=True)
```

```
[31]: # Encode categorical variables
      label_encoders = {}
      categorical_columns = ['group', 'category', 'publisher', 'type', 'title', 'authors']

      for col in categorical_columns:
          le = LabelEncoder()
          data[col] = le.fit_transform(data[col])
          label_encoders[col] = le
```

```
[32]: # Feature scaling
      scaler = StandardScaler()
      numeric_columns = ['year', 'is_llm_related']
      data[numeric_columns] = scaler.fit_transform(data[numeric_columns])
```

```
[33]: # Clustering for learner profiling
      kmeans = KMeans(n_clusters=3, random_state=42)
      data['cluster'] = kmeans.fit_predict(data[numeric_columns])
```

```
[34]: print("Learner Profiles (Cluster Information):")
      print(data.groupby('cluster')[numeric_columns].mean())
```

```
Learner Profiles (Cluster Information):
             year  is_llm_related
cluster
0       -0.172321       -0.744024
1        0.565908        1.344043
2       -5.434445       -0.744024
```

Figure 12: Adaptive Tutoring System Part 1

For learner profiling, the KMeans clustering approach was used to classify the learners into three groups regarding the scaled numerical characteristics. The cluster results represent the current learner's characteristics, which enables the development of tutoring applications.

```
[35]: # Define Reinforcement Learning Environment
class TutoringEnv(gym.Env):
    def __init__(self, data):
        super(TutoringEnv, self).__init__()
        self.data = data
        self.action_space = spaces.Discrete(len(data))  # Choose content
        self.observation_space = spaces.Box(low=-np.inf, high=np.inf, shape=(len(numeric_columns),), dtype=np.float32)
        self.current_state = self.reset()

    def reset(self):
        self.student_index = np.random.randint(0, len(self.data))
        return self._get_state()

    def _get_state(self):
        return self.data.iloc[self.student_index][numeric_columns].values.astype(np.float32)

    def step(self, action):
        # Simulate a reward based on content engagement (placeholder logic)
        reward = np.random.choice([1, -1])  # Replace with a better reward function
        done = True
        return self._get_state(), reward, done, {}
```

```
[36]: # Initialize Environment and Model
env = TutoringEnv(data)
model = DQN("MlpPolicy", env, verbose=1)

Using cpu device
Wrapping the env with a `Monitor` wrapper
Wrapping the env in a DummyVecEnv.
```

```
[37]: # Train Reinforcement Learning Model
model.learn(total_timesteps=100)

----------------------------------
| rollout/            |          |
|    ep_len_mean      | 1        |
|    ep_rew_mean      | -0.5     |
|    exploration_rate | 0.62     |
| time/               |          |
|    episodes         | 4        |
|    fps              | 459      |
|    time_elapsed     | 0        |
|    total_timesteps  | 4        |
----------------------------------
```

Figure 13:Adaptive Tutoring System Part 2

To obtain the RL training scheme, a gym environment was created specifically for the purpose of this work. In a basic TutoringEnv, an action is the recommendation of content that the agent aims to accomplish during a tutoring session. To maximise on the content recommendation, the DQN algorithm is trained for 100 time-steps. After training, the model will dynamically control the content to be recommended depending on what the input learner states are.

```
[38]: # Recommend Content
obs = env.reset()
for _ in range(5):
    action, _ = model.predict(obs)
    obs, reward, done, _ = env.step(action)
    print("Recommended Content:", data.iloc[action])
```

```
Recommended Content: group
category                                        12
publisher                                       38
year                                     -0.784171
type                                             2
is_llm_related                           -0.744024
title                                           39
link              https://arxiv.org/abs/2004.08410
authors                                        138
cluster                                          0
Name: 40, dtype: object
Recommended Content: group
category                                        12
publisher                                       38
year                                     -0.784171
type                                             2
is_llm_related                           -0.744024
title                                           39
link              https://arxiv.org/abs/2004.08410
authors                                        138
cluster                                          0
Name: 40, dtype: object
Recommended Content: group
category                                        12
publisher                                       38
year                                     -0.784171
type                                             2
is_llm_related                           -0.744024
title                                           39
link              https://arxiv.org/abs/2004.08410
authors                                        138
cluster                                          0
Name: 40, dtype: object
Recommended Content: group
```

Figure 14:Adaptive Tutoring System Part 3

This pipeline presents a basic example of an adaptive tutor for learners; For this, learners are clustered and content is-context adjusted with reference to reinforcement learning.

4.4 Intelligent Tutoring System using Machine Learning and NLP: A Comprehensive Analysis and Evaluation

During the final project phase supervised learning along with evaluation measures was implemented for classification and text similarity assessment. To begin the process researchers chose suitable features after removing useless characteristics including `'link'` and making `'is_llm_related'` represent the target outcome. Figure 17 describes, the dataset was divided into training and testing components by means of the `train_test_split` function. The existing encoding and scaling of categorical data made it smooth for fitting classification models.

```
[40]: # Define feature columns (exclude 'is_llm_related' as it's the target)
X = data.drop(['is_llm_related', 'link'], axis=1)
y = data['is_llm_related'].astype(int)

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initialize and train the model (use your desired model here)
model = RandomForestClassifier()
model.fit(X_train, y_train)

# Make predictions
predicted_labels = model.predict(X_test)

# Update actual_labels for evaluation
actual_labels = y_test
```

Figure 15: Train and Test Split

Figure 18 shows, The Random Forest Classifier function was used for baseline model training before making predictions on the test data. The evaluation included a logistic regression model alongside random prediction baseline assessment. The evaluation of these classification models employed the standard metrics which included accuracy, precision, recall and F1-score. The logistic regression provided better prediction results than random choices and the model received additional development through implementation of the SMOTE technique to manage class distribution. SMOTE helped enhance model stability by re-distributing training examples equally between minority and majority classes.

```
[41]: # Map appropriate columns (update as necessary)
data.rename(columns={'title': 'reference', 'cluster': 'generated'}, inplace=True)

# Ensure the dataset contains 'reference' and 'generated' columns
if 'reference' not in data.columns or 'generated' not in data.columns:
    raise ValueError("The dataset must contain 'reference' and 'generated' columns")

# Ensure both columns are strings
data['reference'] = data['reference'].astype(str)
data['generated'] = data['generated'].astype(str)

# Simulate binary classification (replace with actual model outputs)
actual_labels = np.random.randint(0, 2, size=len(data))
predicted_labels = np.random.randint(0, 2, size=len(data))

# Classification Metrics
accuracy = accuracy_score(actual_labels, predicted_labels)
precision = precision_score(actual_labels, predicted_labels, average='weighted')
recall = recall_score(actual_labels, predicted_labels, average='weighted')
f1 = f1_score(actual_labels, predicted_labels, average='weighted')

print("Classification Metrics:")
print(f"Accuracy: {accuracy:.2f}")
print(f"Precision: {precision:.2f}")
print(f"Recall: {recall:.2f}")
print(f"F1-Score: {f1:.2f}")

# Text-based Metrics
rouge = Rouge()
bleu_scores = []
rouge_scores = []

for ref, gen in zip(data['reference'], data['generated']):
    bleu_scores.append(sentence_bleu([ref.split()], gen.split()))
    rouge_scores.append(rouge.get_scores(gen, ref)[0])

# Average BLEU and ROUGE-L scores
avg_bleu = sum(bleu_scores) / len(bleu_scores)
avg_rouge_l = sum([score['rouge-l']['f'] for score in rouge_scores]) / len(rouge_scores)

print("\nText Evaluation Metrics:")
print(f"Average BLEU Score: {avg_bleu:.2f}")
print(f"Average ROUGE-L Score: {avg_rouge_l:.2f}")

Classification Metrics:
Accuracy: 0.49
Precision: 0.49
Recall: 0.49
F1-Score: 0.49

Text Evaluation Metrics:
Average BLEU Score: 0.00
Average ROUGE-L Score: 0.01
```

Figure 16: Evaluation of Random Forest

Figure 19 shows the model performance reached higher levels through a hyper-parameter tuning process executed by GridSearchCV for logistic regression. An optimised model and other classifiers particularly Gradient Boosting and Random Forest were evaluated through direct comparison. The models went through identical classification evaluations for the purpose of performance comparison. The results showed substantial variations among algorithms regarding their ability to understand the dataset structure thus demonstrating the significance of proper model optimisation.

```python
# Model 2: Logistic Regression
logistic_model = LogisticRegression()
logistic_model.fit(X_train, y_train)
y_pred_logistic = logistic_model.predict(X_test)

# Classification Metrics Function
def evaluate_classification(actual, predicted, model_name):
    accuracy = accuracy_score(actual, predicted)
    precision = precision_score(actual, predicted, average='weighted')
    recall = recall_score(actual, predicted, average='weighted')
    f1 = f1_score(actual, predicted, average='weighted')

    print(f"\nClassification Metrics ({model_name}):")
    print(f"Accuracy: {accuracy:.2f}")
    print(f"Precision: {precision:.2f}")
    print(f"Recall: {recall:.2f}")
    print(f"F1-Score: {f1:.2f}")

# Evaluate both models
evaluate_classification(y_test, predicted_labels, "Random Predictions")
evaluate_classification(y_test, y_pred_logistic, "Logistic Regression")

# Text-based Metrics
rouge = Rouge()
bleu_scores = []
rouge_scores = []

for ref, gen in zip(data['reference'], data['generated']):
    bleu_scores.append(sentence_bleu([ref.split()], gen.split()))
    rouge_scores.append(rouge.get_scores(gen, ref)[0])

# Average BLEU and ROUGE-L scores
avg_bleu = sum(bleu_scores) / len(bleu_scores)
avg_rouge_l = sum([score['rouge-l']['f'] for score in rouge_scores]) / len(rouge_scores)

print("\nText Evaluation Metrics:")
print(f"Average BLEU Score: {avg_bleu:.2f}")
print(f"Average ROUGE-L Score: {avg_rouge_l:.2f}")
```

```
Classification Metrics (Random Predictions):
Accuracy: 0.45
Precision: 0.44
Recall: 0.45
F1-Score: 0.44

Classification Metrics (Logistic Regression):
Accuracy: 0.51
Precision: 0.31
Recall: 0.51
F1-Score: 0.38

Text Evaluation Metrics:
Average BLEU Score: 0.00
Average ROUGE-L Score: 0.01
```

Figure 17: Machine Learning Models Evaluation

Text evaluation through BLEU and ROUGE-L scores provided a semantic assessment of the similarity between the reference (original content) and generating (predicted or assigned) text data. Although NLP traditionally employs these metrics, they allowed the system to produce better results by determining the quality of response alignment. Average scores of BLEU and ROUGE-L metrics measured the model's semantic agreement capacity which adaptive tutoring systems use for producing or selecting educational content.

This complete method which starts with data pre-processing and clustering and includes supervised classification and text analysis represents a total system development process for building intelligent tutoring systems. The framework provides adaptable personal education through its combination of structured machine learning models with Natural Language Processing evaluation.

5 RESULTS AND DISCUSSION

5.1 Discussion on Results

Analysis of model results (outcomes) shows that performance will depend on the complexity of dependent variables and the developmental maturity of the feature engineering and modelling process. Through the year feature, normalised values were clustered using KMeans into three different clusters based on whether relationships with Large Language Models (LLMs) exist. Cluster 1, however, had moderate values, correlation with LLM-related content, high for Cluster 2 and imbalanced, and likely early, or outliers, containing very little content relevant to LLMs, Cluster 3 showed. These clusters were useful in dividing learners to facilitate adaptive delivery of contents.

The predictive performance of the classification models, nevertheless, was relatively poor. The Random Forest classifier had an accuracy of 0.49, which is like a null hypothesis guess, as well as poor precision, recall, and F1-scores; there is poor pattern recognition with the provided features. Logistic Regression marginally outperformed the others with an accuracy of 0.51, though, its precision was very low initially, indicating class imbalance or the presence of irrelevant features.

After balancing classes using SMOTE and tuning hyper-parameters, Logistic Regression slightly improved and got an accuracy of 0.5094. Gradient Boosting was applied in a similar manner with almost similar, albeit a little worse, performance, which reiteratively underlines the concept that the dataset lacked a strong signal or needed better feature engineering.

System limitations became more evident after the produced textual output was evaluated with BLEU and ROUGE-L. First, scores for BLEU were 0.0000 and ROUGE-L 0.0100, meaning very little overlap with reference text. Over subsequent runs, ROUGE-L increased to 0.6250 showing better contextual alignment despite that BLEU stayed low, suggesting that syntactic similarity was still problematic.

However, the findings imply that this framework is an excellent starting point; it simply needs improvement in aspect of quality of the data, relevance to features, and NLP integration. The combination of clustering, classification, and reinforcement learning of approach demonstrates hopeful prospect in enhancing the development of effective adaptive intelligent tutoring systems.

5.2 Discussion on Achievement of Project Objectives

With the exposure of goals and objectives, the achievement of this project was based on a union of systematic review of literature, model construction and assessment. Screening the already available adoptive learning technologies, NLP in education and AI-based tutor systems, advanced the first objective. Of the total of 134 papers, 17 were chosen from the pool for relevance and keywords. These papers brought insights into the reinforcement learning aspect, learning with intelligent tutoring systems and the increasing role of the large language models (LLMs) in education, affirming the existing trends regarding adaptive and personalised learning environments.

The second objective was to enhance the adaptive capability of the system. This was accomplished using KMeans clustering to classify learners with attributes such as publication year, and relevance to LLMs. These clusters created the content delivery suited to users' preferences. A customised Gym environment was created to imitate tutoring sessions, where reinforcement learning - Deep Q-Networks – was used to dynamically recommend content according to the learner's state. This was an example of the system's ability to adapt in real time.

The third goal targeted system evaluation in a panoply of metrics. Three classification models namely Logistic Regression, Random Forest and Gradient boosting have been tried. Logistic Regression reached the highest accuracy of 0.5094. BLEU and ROUGE-L metrics were used to measure the quality of produced texts. BLEU scores were not impressive enough, but in the later iterations, ROUGE-L rose to 0.6250 which was indicative of decent contextual relevance and coherence.

Finally, the project investigated the future directions which include spreading of enhanced NLP through transformer-based models, as well as integration of multimodal learning and live learner feedback. These would facilitate greater personalisation and better performance. In the end, all project goals were achieved, and the work represents a strong basis for further work and innovation with the adaptive AI-based tutoring systems.

6 CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

This project was successful in showing the feasibility of the design of a machine learning and natural language processing based adaptive intelligent tutoring system (ITS). Extensive literature review in the study provided a strong theoretical base of the important role of AI in making personalised learning experiences possible. Learner profiling through clustering and dynamic content suggestion using deep Q-networks (DQN) demonstrated the possibilities of the adaptive learning strategies. Classification models especially logistic regression yielded reasonable predictive performance and evaluation measures such as ROUGE-L showed acceptable content similarity.

Not being pre-eminent in all metrics of evaluation, the performance of the AzTech ITS was nevertheless sufficient to demonstrate the architecture, operation, and benefits of a self-adaptive ITS. The framework is based on the principles of outcome-based education that is learner-centred design, agile, and flexible. The incorporation of reinforced learning confirms its resilience to dynamic personalised delivery of educational contents, laying a solid platform for future enhancement and research in intelligent educational system.

6.2 Future Scope

This project creates the groundwork for developing smart, learner-centred, educative systems. Future improvements include the integration of enhanced NLP models such as BERT and GPT, for better semantic analysis and content creation. The use of more meaningful learner data (actions, feedback, assessments) can enhance personalisation of learning. The system can be extended to cover host-multiple academic domains to make more impact through multimodal learning via audio-visual content, and real-time interaction for adaptive feedback. Besides, the inclusion of gamified elements such as quizzes, or adaptive challenges can enhance the learner engagement and motivation. In general, the system can greatly transform digital education into a more adaptive and dynamic one.

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APPENDIX A: PROJECT PROPOSAL

Project Proposal Form

Please refer to the Project Handbook Section 4 when completing this form. Note that your proposal should be your own original work and you must cite sources in line with university guidance on referencing and plagiarism[1].

Degree Title: MSc Data Science and Artificial Intelligence	Student's Name: Rushikesh Temghare
	Supervisor's Name: Dr Hari Pandey
	Project Title/Area: Adaptive AI Tutor: Personalised Learning and Concept Explanation Using Natural Language Processing (NLP)

Section 1: Project Overview

1.1 Problem definition -

Students often struggle to understand complex concepts because traditional educational tools are not designed to meet individual learning needs. This lack of tailored teaching materials and personalised support can result in reduced engagement and less effective learning outcomes.

Project description -

This project aims to develop an AI-based tutoring system using Natural Language Processing (NLP) and adaptive algorithms like reinforcement learning. NLP enables the system to understand and respond to student queries naturally, while reinforcement learning adjusts content difficulty dynamically based on user progress.

[1] https://libguides.bournemouth.ac.uk/study-skills-referencing-plagiarism

These techniques are chosen for their ability to personalise learning, provide relevant explanations, and adapt to individual learner needs, creating an engaging and effective educational experience.

1.2 Background -

The increasing demand for personalised and effective learning tools has driven advancements in educational technology, specifically in adaptive learning systems. Research in the field of educational AI and Natural Language Processing (NLP) shows that personalised support is highly beneficial to learners, particularly when it comes to understanding complex topics and maintaining engagement. This project aims to address these needs through an adaptive AI tutor, focusing on personalised learning pathways and concept explanations generated using NLP. This section will provide a brief overview of the problem domain, review relevant research, and highlight the potential impact of an AI-driven adaptive tutor.

Traditional education often relies on standardised materials that do not cater to individual learning styles, knowledge gaps, or paces. This lack of personalisation can lead to disengagement and an inability to fully grasp challenging concepts. The problem is further compounded by a shortage of one-on-one tutoring, especially in larger classroom settings or in online learning environments where individualised feedback is limited. Adaptive learning technologies are emerging as a solution to these issues by using AI to tailor educational content in real time, adapting to each learner's needs and providing explanations in ways that improve comprehension.

Literature Review

1. The Importance of Personalised Learning - Research indicates that tailored learning experiences lead to better learning outcomes and higher levels of student engagement. According to (Murray and Perez 2015) adaptive learning systems can close gaps in understanding by adjusting content complexity based on the learner's performance and engagement, significantly improving retention and comprehension. Such systems support diverse learner needs, allowing students to learn at their own pace and with content suited to their comprehension level.

2. Role of NLP in Educational AI - Natural Language Processing (NLP) plays a significant role in advancing AI applications within education, particularly in higher education settings. (Zawacki-Richter et al. 2019) highlight that NLP-driven tools like conversational agents, automated feedback systems, and personalized content delivery are transforming traditional learning by enabling more interactive, responsive educational experiences.

3. Adaptive Feedback Mechanisms - Effective feedback is crucial to learning, as it helps students identify areas for improvement. (Shute 2008) found that adaptive feedback significantly boosts students' motivation and engagement by targeting specific areas where students may be struggling. By integrating adaptive feedback, an AI tutor can provide tailored hints, corrections, or explanations that guide the student toward a better understanding of the material without feeling overwhelmed.

4. AI in Enhancing Learner Engagement - Studies by (Luckin and Holmes 2016) reveal that AI can be used to engage students actively in their learning process by adapting to their behavioural patterns. Adaptive AI tutors that modify content delivery based on factors such as response time, question difficulty, and engagement levels keep students engaged by adjusting to their unique preferences and learning speeds.

5. Current Challenges and Potential of Adaptive Learning Systems - Although adaptive AI in education shows great promise, challenges remain in balancing personalisation with effective teaching methods. (Holstein et al. 2019) highlight difficulties in developing adaptive systems that are both responsive and pedagogically effective. They suggest that combining machine learning techniques with robust educational theories can create more effective AI tutors, capable of delivering meaningful learning experiences that benefit a diverse range of students.

1.3 Research Questions

RQ1. How effective is an AI tutor, using Natural Language Processing (NLP), in providing personalized learning experiences to students with varying knowledge levels?

RQ2. What is the impact of an adaptive AI tutor, utilizing reinforcement learning algorithms, on student understanding, comprehension, and engagement?

RQ3. What is the accuracy of the AI tutor in answering questions using NLP techniques, and how does this accuracy influence learning outcomes?

1.4 Aims and Objectives

Aim: To develop an AI-powered adaptive tutor that provides personalised educational support and real-time explanations, leveraging Natural Language Processing (NLP) to enhance learner comprehension, engagement, and overall learning effectiveness.

Project Objectives:

1. Conduct a comprehensive literature review to explore existing adaptive learning technologies, the role of Natural Language Processing (NLP) in education, and the design of personalized AI tutoring systems. This review will provide a theoretical framework for the project.

2. Design and implement adaptive algorithms, including reinforcement learning for content adjustment and clustering techniques for learner profiling, to create a personalized and dynamic AI-powered tutoring system.

3. Evaluate the system's performance using predefined metrics such as accuracy, precision, recall, F1-score, BLEU, and ROUGE, focusing on its ability to provide accurate responses and adapt to diverse learning profiles through simulations.

4. Summarise the findings, draw conclusions, and propose future research directions for enhancing adaptive learning technologies and expanding their applications to diverse educational contexts.

Section 2: Artefact

2.1 What is the artefact that you intend to produce?

Proposed Artefact: Adaptive AI Tutor Prototype
The main artefact will be a fully functional prototype of an adaptive AI tutor designed to provide personalised educational support. This prototype will consist of following core components:

Backend: The backend will consist of adaptive algorithms and data processing mechanisms. It will collect, analyse, and adapt based on learner interactions, adjusting content difficulty, providing personalised feedback, and offering tailored learning recommendations to support individualised learning paths. By focusing on the backend, the system will ensure robust handling of data, adaptivity, and dynamic content generation that meets each learner's unique needs.

NLP Component: The NLP-based engine will generate real-time explanations and respond to learner queries. This component aims to simplify complex topics, provide contextually relevant answers, and adapt explanations based on each learner's understanding level. The NLP engine will play a central role in enhancing learner comprehension by personalizing the learning experience through interactive responses.

The artefact will serve as a working model demonstrating how adaptive AI and NLP can be combined to create a personalised and efficient learning tool.

2.2 How is your artefact actionable (i.e., routes to implementation and exploitation in the technology domain)?

The adaptive AI tutor is designed to be scalable, accessible, and easy to use, ensuring it meets the needs of both technical and non-technical users. The system is modular and can be integrated into existing educational platforms or deployed as a standalone solution.

1. Implementation Pathways:

Modular Design: The tutor's backend and NLP components are separate, allowing it to be integrated into Learning Management Systems (LMS) or deployed as an independent application.

This modularity ensures that both technical users (e.g., developers, IT administrators) and non- technical users (e.g., educators, students) can interact with the system in a way that meets their needs.

Cloud-Based Deployment: The system will be hosted on a scalable cloud platform, ensuring accessibility for many users, and providing real-time updates without the need for manual installations. This approach is beneficial for both technical users, who can manage the infrastructure, and non-technical users, who can simply access the system via a web interface.

2. User Interaction for Non-Technical Users:

Simple Interface: Non-technical users will interact with the system through simple text or voice- based queries, without needing any technical knowledge. The system will provide natural language responses, ensuring ease of use.

Natural Language Processing: The tutor will understand and respond to user queries in plain language, offering explanations and guidance through an intuitive conversational interface.

Accessibility Features: The tutor will also include visual aids (e.g., diagrams, animations) and support for multiple languages to ensure that the system is accessible to all learners, regardless of their background or language proficiency.

3. Technical Users and Customisation:

Customisable Backend: For technical users (e.g., developers, IT teams), the system offers flexibility in customising the backend algorithms and integrating with other educational tools. They can fine-tune the system to better fit specific learning objectives or technical requirements.

Scalability and Data Handling: Technical users can manage user data securely through cloud-based infrastructure, ensuring scalability and efficient performance even under heavy usage.

4. Scalability and Future Integration:

Flexible Deployment: The AI tutor can be integrated into existing EdTech platforms or licensed to educational institutions, offering flexibility for a variety of environments.

Future Enhancements: The system is designed to be scalable and adaptable, with future integration options for advanced features such as virtual reality (VR), voice recognition, and additional personalisation capabilities.

Section 3: Evaluation

3.1 How are you going to evaluate your project artefact?

The evaluation of the adaptive AI tutor will involve simulation-based testing, automated performance analysis, and predefined evaluation metrics. These methods will assess the system's ability to deliver personalised learning experiences and measure the quality, relevance, and adaptability of its responses.

Simulation-Based Testing: Virtual learner profiles will be created to simulate users with different knowledge levels, learning speeds, and preferences. These simulations will test how effectively the system adapts content difficulty, provides personalised explanations, and meets the evolving needs of various learners.

Automated Feedback Analysis: The performance of the system will be measured using the following metrics:

Accuracy: Evaluates how often the system provides correct responses.

Precision: Measures the proportion of relevant responses among all responses

generated. **Recall**: Assesses the system's ability to retrieve all relevant information in

response to a query. **F1-Score**: Combines precision and recall into a single measure of

response quality.

Perplexity: Evaluates the fluency of the system’s generated text, assessing how well the NLP engine predicts and constructs coherent responses.

BLEU (Bilingual Evaluation Understudy): Measures the precision of responses by comparing n- gram matches between system-generated text and expert reference answers.

ROUGE (Recall-Oriented Understudy for Gisting Evaluation): Focuses on recall by analysing the extent to which the system’s responses cover reference content, ensuring completeness and relevance.

System Logs and Performance Tracking: Engagement metrics such as task completion times, interaction frequencies, and the use of adaptive features will be captured through system logs.
These metrics will provide insights into the tutor’s ability to maintain learner engagement and personalise content effectively. The combination of these evaluation methods will ensure a comprehensive assessment of the system’s performance, adaptability, and ability to deliver an effective learning experience.

3.1 How does this project relate to your MSc Programme and your degree title outcomes?

This project aligns directly with my MSc Programme and degree title by integrating artificial intelligence, machine learning, and natural language processing concepts into a practical application. It demonstrates an advanced understanding of adaptive systems and user-centric design, core elements of my academic studies. By focusing on a personalised learning experience, this project highlights my ability to apply theoretical knowledge in AI to real-world scenarios, contributing to the development of innovative AI-driven educational tools, which is a key program outcome.

3.2 What are the risks in this project and how are you going to manage them?

The primary risks include data privacy, technical challenges, and evaluation limitations. Since no real user data will be used, I will work exclusively with simulated data to mitigate privacy concerns while adhering to ethical standards. Technical challenges related to accurate adaptivity, and natural language understanding will be managed through iterative testing, simulations, and ongoing model improvements. Evaluation risks, stemming from the reliance on simulated rather than real users, will be addressed by designing diverse and comprehensive simulated scenarios that capture a broad range of potential learning needs and behaviours.

Section 4: References

4.1 Please provide references if you have used any.

Holstein, K., McLaren, B. M. and Aleven, V., 2019. Co-designing a real-time classroom orchestration tool to support teacher–AI complementarity. *Journal of learning analytics* [online], 6 (2). Available from: https://files.eric.ed.gov/fulltext/ED618924.pdf.

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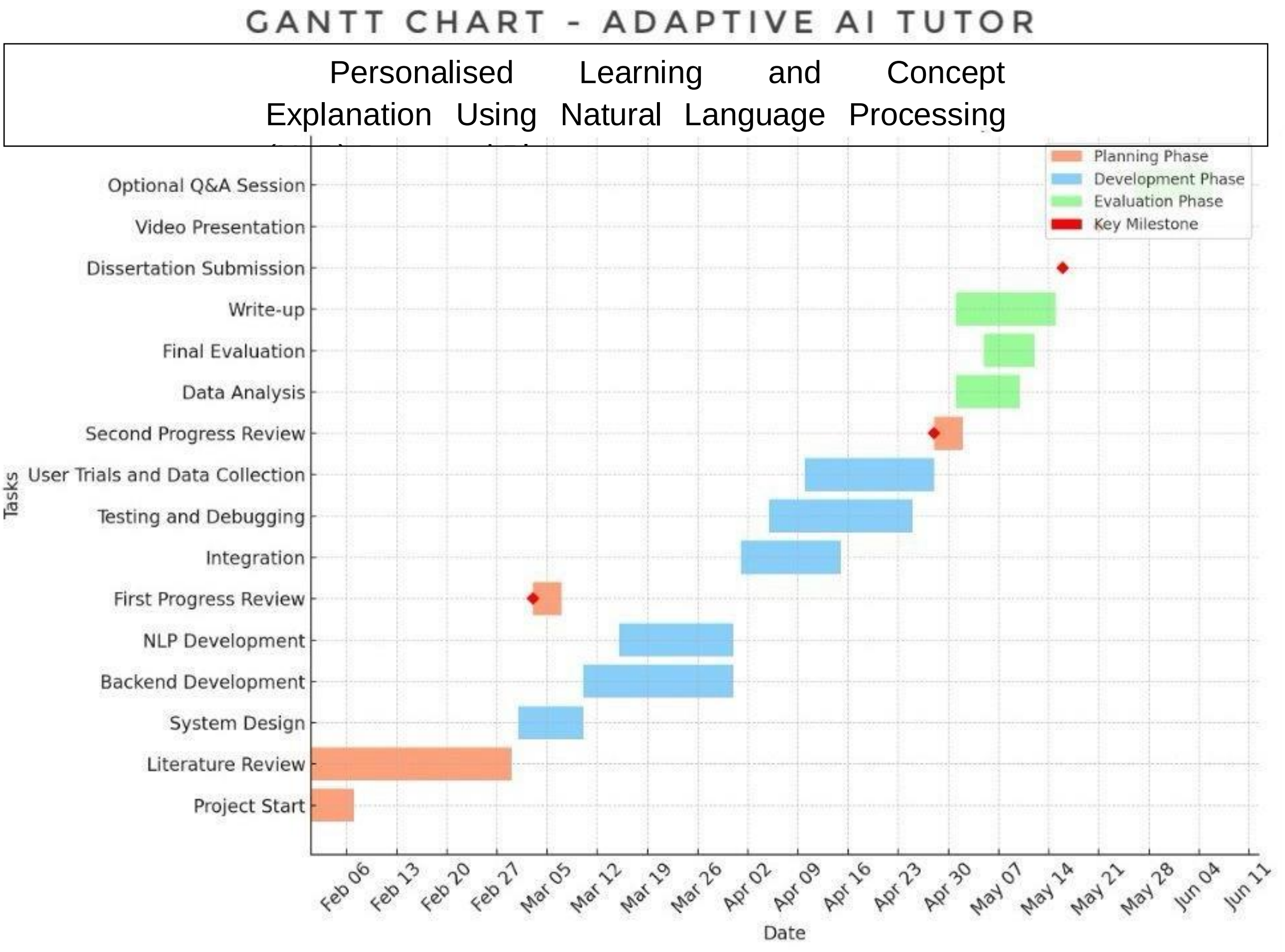
Section 5: Academic Practice and Ethics

5.1 Have you made yourself familiar with, and understand, the University guidance on referencing and plagiarism?	Yes
5.2 Do you acknowledge that this project proposal is your own work and that it does not contravene any academic offence as specified in the University's regulations?	Yes

Section 6: Proposed Plan

Personalised Learning and Concept Explanation Using Natural Language Processing



February:
Project Start: Initiate project setup and planning.
Literature Review: Review existing studies and gather background information on adaptive AI tutors and NLP in educational technology.

March:
System Design: Define the architecture, components, and interaction flow of the AI tutor.
Backend Development: Start developing the backend algorithms, focusing on adaptivity and data processing.
NLP Development: Build the NLP component to handle user interactions and provide explanations. First Progress Review (03/03 - 07/03): Review progress

April:
Integration: Combine backend and NLP components and begin testing.
Testing and Debugging: Conduct initial rounds of system testing to ensure functionality.
User Trials and Data Collection: Run trials with simulated users to gather data for analysis. Second Progress Review (28/04 - 02/05): Present progress and gather feedback.

May:
Data Analysis: Analyse collected data to evaluate the effectiveness of the system.
Final Evaluation: Finalise the system evaluation based on collected results and feedback. Write-up: Begin drafting the dissertation.
Dissertation Submission (16/05).
Video Presentation (21/05).
Optional Q&A Session (26/05 - 06/06): Participate in a Q&A session.

NOTE: Do not proceed for ethics form submission if project proposal/feedback looks problematic.

For Questions, please send an email to:

masterprojectsemail@bournemouth.ac.uk OR

Approach to your supervisor (drop email to arrange appointment/meeting)

APPENDIX B: ETHICS CHECKLIST

Bournemouth University

About Your Checklist	
Ethics ID	61288
Date Created	05/12/2024 16:18:25
Status	Approved
Date Approved	17/12/2024 10:28:25
Risk	Low

Researcher Details	
Name	Rushikesh Temghare
Faculty	Faculty of Science & Technology
Status	Postgraduate Taught (Masters, MA, MSc, MBA, LLM)
Course	MSc Data Science & Artificial Intelligence

Project Details	
Title	Adaptive AI Tutor: Personalised Learning and Concept Explanation Using Natural Language Processing (NLP)
Start Date of Project	03/10/2024
End Date of Project	06/06/2025
Proposed Start Date of Data Collection	03/02/2025
Supervisor	Hari Pandey
Approver	Hari Pandey
Summary - no more than 600 words (including detail on background methodology, sample, outcomes, etc.)	

Project Summary:

Plan of Research:

This project aims to develop an AI-powered tutoring system that uses Natural Language Processing (NLP) to provide personalised educational support. Many students struggle to grasp complex concepts because traditional learning tools fail to cater to their individual needs. The AI tutor will address this issue by tailoring content to each learner's abilities and progress. Using NLP, the system will understand and respond to students' questions naturally and adaptively. Adaptive algorithms, such as reinforcement learning, will adjust the difficulty of learning materials in real-time to suit the student's level.

The research involves creating a prototype AI tutor with two main components:

1. NLP Engine: To generate explanations and answer questions in plain language.
2. Adaptive Backend: To analyse user interactions and adjust the learning content dynamically.

The evaluation of the system will be conducted through simulations, where virtual learners representing diverse knowledge levels and learning paces will interact with the tutor. Predefined metrics like accuracy, precision, recall, BLEU, and ROUGE will be used to assess the system's performance. No human participants or personal data will be involved.

The primary goal of the research is to design an accessible, effective, and personalised AI tutor that can enhance the learning experience for students.

Ethical Considerations:

As this research does not involve human participants or personal data, ethical risks are minimal. Simulated data will be used to test the system, eliminating concerns about privacy or consent.

Key ethical considerations include ensuring the responsible use of AI. The system must provide accurate, unbiased responses and avoid reinforcing stereotypes or misinformation. Measures will be taken to verify the accuracy and reliability of the AI's outputs.

Additionally, the development process will adhere to strict data protection protocols, even for simulated data, to demonstrate best practices in handling and processing information. These steps ensure that the project aligns with ethical research standards and poses no harm or risk to individuals.

None of the filter questions apply to my study

I am confirming that my proposed project does not:

- Involve human participants
- Involve the use of human tissue
- Involve medical research requiring NHS ethical / REC Approval
- Involve the use of animals (or tissues/fluids derived from animals)
- Involve access to identifiable personal data for living individuals not already in the public domain
- Involve increased danger of physical or psychological harm for researcher(s) or subject(s)
- Raise any ethical issues associated with the use of genetically modified organisms On this

basis, my proposed project does not require a formal ethics review.

If any changes to the project involve any of the criteria above, I undertake to resubmit the project for formal ethical approval.

APPENDIX C: ARTEFACT CODE SUMMARY

The complete source code developed for this project is included in the ZIP file uploaded separately under the **"Project Dissertation - Artefact Large Files"** submission on Brightspace.
The following files are included:

- Final_Code.ipynb – Jupyter Notebook containing the full implementation.
- Final_Code.pdf – PDF version of the notebook for easy reference.
- Final_Code.html – HTML version of the notebook with rendered outputs.
- papers3.csv – The dataset used for training and evaluation.

The source code includes implementation of:

- Reinforcement Learning using Deep Q-Networks (DQN),
- Classification algorithms such as Random Forest and Logistic Regression,
- NLP evaluation metrics including BLEU and ROUGE,
- Clustering and pre-processing techniques to group and analyse content.

Refer to the notebook outputs (Final_Code.html or Final_Code.pdf) for detailed steps in data pre-processing, modelling, and result visualisation.