Enhancing Personalized Learning Experiences through AI-driven Analysis of xAPI Data

تعزيز تجربة التعلم عن طريق تحليل بيانات تجربة التعلم بواسطة الذكاء الاصطناعي

by

HANEEN ODEH

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Abstract

In today's evolving educational arena, Adaptive learning experiences to individual needs has become a focal point. The Experience API (xAPI) provides a comprehensive mechanism to document all types of learning interactions, storing this stream of data into the Learning Record Store (LRS). This dissertation explores the fusion of Artificial Intelligence (AI) techniques with the obtained xAPI data. There is a gap of research in utilizing xAPI and AI integration in addressing learning objectives and understanding learners cognitive state and the utilization of data in actionable manner. This paper recommends a competency-aware framework for integrating xAPI and AI that predicts the pass/fail status of every student and provides personalized actionable feedback in an autonomous manner and in human-friendly language. To achieve this goal the CRISP-DM methodology was utilized. The analysis examined an elearning lesson with 153 records and 51 participants, it concluded that blooms-level and pre-assessments are reliable predictors of student performance. The classification algorithms were able to predict the pass/fail statues with up to 93.5% accuracy. These predictions were fed to chatGPT that provided personalized actionable feedback to students. The findings of this study can offer valuable insights for Educators, e-learning professionals, and AI researchers, showcasing the potential of AI in transforming the future of adaptive learning.

Keywords: xAPI, educational data mining, AI

خلاصة

في ساحة التعليم المتطورة اليوم، أصبحت تجارب التعلم المتكيفة مع الاحتياجات الفردية نقطة محورية. توفر واجهة برمجة التطبيقات لرصد التجربة التعليمية آلية شاملة لتوثيق جميع أنواع تفاعلات التعلم، وتخزين سلسلة البيانات تلك في مخزن سجلات التعلم. تستكشف هذه الأطروحة دمج تقنيات الذكاء الاصطناعي مع البيانات التي يتم تحصيلها من تجربة التعلم. هنالك فجوة في الأبحاث السابقة تخص الاستعانة ببيانات تجربة التعلم ودمجها مع تكنولوجيا الذكاء الاصطناعي بما يخص نقاط التعلم وفهم حالة الاستيعاب لدى المتعلم بصورة تطبيقية. هذه الورقة تقترح نظام عمل ذو خواص معرفية يدمج بيانات تجربة التعلم مع الذكاء الاصطناعي لتوقع حالة النجاح أو الرسوب للطلبة على مستوى النقاط التعليمية ويقدم تغذية راجعة قابلة للتطبيق بصورة تلقائية وبلغة يسهل للإنسان فهمها. لتحقيق هذا الهدف تمت الاستعانة بمنهجية العملية قياسية عبر الصناعات لاستخراج البيانات. في مرحلة تحليل البيانات تم فحص درس إلكتروني نتج عنه 153 سجل و51 مشارك، استنتج منه أن درجة بلوم والتقييمات المسبقة هي مؤشر موثوق للتنبؤ بنتائج الطلبلة. كانت خوارزمية التصنيف قادرة على التنبؤ حالة النجاح أو الرسوب بنسبة 93.5% من الصحة .هذه التوقعات تم إدخالها للشات جي بي تي الذي بدورة قام بتوفير تغذية راجعة شخصية وعملية للطلبة. يمكن أن تعطي نتائج هذه الدراسة منظوراً قيماً للمعلمين والمتخصصين في التعلم الإلكتروني والباحثين في مجال الذكاء الاصطناعي، مما يعرض إمكانات الذكاء الاصطناعي في تحويل مستقبل التعلم التكيفي

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List of Abbreviations

ADL	Advanced Distributed Learning
CNN	Convolutional Neural Network
CRISP-DM	CRoss Industry Standard Process for Data Mining
DT	Decision Tree
EDA	Exploratory Data Analysis
GLA	Gaming Learning Analytics
KNN	k-Nearest Neighbors
LA	Learning Analytics
LMS	Learning Management System
LR	Logistic Regression
LRS	Learning Record Store
ML	Machine Learning
NN	Neural Network
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
RF	Random Forest
STEM	Science, technology, engineering, and mathematics
SVM	Support Vector Machines
UI	User Interface
VQL	Veracity Query Language
xAPI	Experience API
xAPI-SG	Experience API for Serious Games

Chapter 1: Introduction

Presents the following:

- Background and Context Overview
- Research Motivation.
- Problem Definition.
- Aims and Objectives.
- The Research Questions.
- Significance and Limitations.
- Outline of the Dissertation.

1.1 Background and Context Overview

With the swift progression of technology, the realm of education has undergone notable transformations, especially in e-learning. The Experience API (xAPI) stands out as a crucial tool for tracking and documenting learning experiences, offering an in-depth view of a learner's journey (Rustici Software, n.d.). Simultaneously, Artificial Intelligence (AI) has showcased its potential across various sectors, including education, where it aspires to reshape personalized learning experiences (Holmes & Tuomi, 2022).

This research presents a proof-of-concept of an xAPI-AI integration framework. There has been limited research on the use of xAPI, especially in AI-related contexts. The research also suggests a more sophisticated model that considers both the difficulty of the learning task and the student's interactions with the material. Most of the previous research captured the UI-

related interactions with the learning material and struggled to map competencies and learning objectives. To achieve this task, a login page created for this study simulates a Learning Management System (LMS) and used to assign students to a lesson that tracks student activity and integrates teaching points aligned with Bloom's taxonomy levels. This alignment ensures that the data collected is not only about what students are doing but also reflects the cognitive complexity of their learning tasks. Then, using the data collected and classification algorithms to predict whether a student will pass or fail a learning objective. The research then employs an AI, specifically ChatGPT, to provide personalized feedback to students. This feedback is informed by the predictions about which Bloom's taxonomy level skills students are likely to struggle with. It's an innovative application of AI to directly support student learning. This aspect likely involves recommending resources or strategies tailored to the specific needs of each student, based on the AI's analysis of their performance and predicted challenges.

The research potentially contributes significant insights into personalized learning. By leveraging AI and xAPI data, exploring how technology can adaptively support students, providing real-time, customized feedback and guidance that aligns with their learning needs. In conclusion, this dissertation presents a new approach to personalized learning, combining the strengths of AI, xAPI data analysis, and educational theory. It’s a valuable contribution to the field of educational technology and AI in education.

The dissertation will be organized into six chapters: introduction, literature review, methodology, results and analysis, discussion, and conclusion.

1.2 Research Motivation.

In the rapidly evolving landscape of educational technology, the integration of Artificial Intelligence (AI) in enhancing personalized learning experiences presents a groundbreaking opportunity. Recent advancements in AI have shown potential in transforming educational methodologies by providing tailored learning experiences based on individual student data (Luckin et al., 2016). The Experience API (xAPI) emerges as a pivotal technology in this context, enabling the tracking of a wide range of learning activities across various platforms (Bakharia et al., 2016). However, the application of AI in interpreting xAPI data to predict and improve student learning outcomes remains underexplored. This gap presents an opportunity to innovate in personalized education, where AI-driven analysis of xAPI data could revolutionize the way educators approach individualized learning. The integration of AI with xAPI data has the potential to offer insights far beyond traditional learning analytics, enabling real-time feedback and adaptive learning experience tailored to individual student needs (Siemens, 2013). By undertaking this research, we aim to demonstrate the feasibility and proof-of-concept of this approach and present a framework of implementation.

1.3 Problem Definition

The contemporary educational landscape faces the challenge of effectively catering to the diverse learning needs and styles of individual students. Traditional educational models often adopt a one-size-fits-all approach, which inadequately addresses these varied requirements (Patricia L. Smith & Tillman J. Ragan, 2012). The advent of digital learning platforms offers a wealth of data on student learning behaviors, yet the sheer volume and

complexity of this data make it challenging to derive actionable insights for personalized learning (Baker & Siemens, 2014). The Experience API (xAPI), a standard for data collection in technology-enabled learning environments, captures a broad spectrum of learner interactions, but its potential for enhancing personalized learning is not fully realized in current practices.

xAPI allows for the collection of data about a wide range of learning experiences, both online and offline, providing a comprehensive view of a learner's journey. When combined with AI-driven analysis, it can transform education.

In most learning scenarios the learners are evaluated through the traditional assessments methods, and data used in learning analysis is dependent on those results. xAPI and AI integration provides autonomous means of evaluating students prior to their assessments whilst in the learning phase to improve performance and plan suitable interventions.

Additionally, while AI has shown promise in education, particularly in personalizing learning experiences, there is a gap in effectively analyzing xAPI data using AI techniques (Ouyang & Jiao, 2021). Current AI applications in education are often limited to basic adaptive learning systems and do not fully exploit the depth of data available through xAPI. Moreover, there is an insufficient exploration of the integration of educational theories, such as Bloom's taxonomy, with AI-driven data analysis to inform tailored educational strategies.

Therefore, this study addresses the critical need for an AI-driven approach that effectively analyzes xAPI data, offering a sophisticated and nuanced understanding of individual learner profiles. By focusing on predictive models that integrate educational theories like Bloom's taxonomy, this research aims to bridge the gap between the rich data available through xAPI and the personalized instructional strategies required in modern

educational settings. The study seeks to explore the application of xAPI data analytics to enhance the personalization of learning experiences, making education more adaptive and responsive to individual learner needs.

1.4 Aims and Objectives.

The primary objective of this research is to explore the use of AI-driven analysis of xAPI data in enhancing personalized learning experiences. This study aims to bridge the gap in current educational methodologies by leveraging the potential of AI to provide customized feedback and predictions for individual student data. Specifically, the study will focus on developing an AI model that can predict student performance using data collected through the xAPI framework. Additionally, this research seeks to examine student learning outcomes per learning objectives, particularly in identifying and addressing areas of struggle. Another crucial goal is to assess the role of Bloom's taxonomy levels in refining the predictive accuracy of the AI model. By achieving these objectives, the study endeavors to contribute significantly to the field of educational technology, proposing a model for personalized education that is both data-informed and learner-centered. The selected methodology of this study is based on the The CRoss Industry Standard Process for Data Mining (CRISP-DM). The targeted demographic is the general public adult learner.

1.5 Research Questions

To fulfill the research objective, the dissertation proposes the following research questions:

1. How can xAPI be integrated with AI technologies?
2. What xAPI attributes contributes to performance prediction?
3. How can learning prediction be utilized in adaptive learning?

1.6 Significance and Limitations

The study represents a cutting-edge blend of AI with xAPI data analysis, advancing the frontier of personalized education technology. Enhancing Personalized Learning by predicting student performance and customizing feedback, which directly contributes to more tailored and effective learning experiences. The use of xAPI data enables a deeper understanding of student learning processes and pinpoints areas of struggle. The model developed could be scalable and adaptable to various educational contexts, making it a valuable tool for a wide range of learning environments. This study adds valuable knowledge to the field of AI in education, particularly in applying AI for predictive analytics and personalized feedback. This contributes to providing foundational knowledge and insight that guides the development of more detailed, comprehensive projects.

However, there are some limitations since this is a proof-of-concept study, it was only able explored a single eLearning lesson with three blooms level. The collection and analysis were limited to the number of participants of the study, they were not registered student and data history was only limited to a that single experience. Additionally, AI algorithms can inherit or develop biases based on the data they are trained on, which could affect the accuracy and fairness of predictions and feedback.

1.7 Outline of the Dissertation

The dissertation has been structured as below:

1. **Chapter 1: Introduction:**

   Presents an overview of the research, context, motivation, problem statement and objectives. Additionally, it poses the research questions which takes under consideration the stated limitations and potential significance in its methodology design.

2. **Chapter 2: Literature Review:**

   A systematic review of literature took place to investigate the integration of xAPI and AI in the literature and to provide background on key technical aspects such as xAPI and educational theories associated with this study.

3. **Chapter 3: Methodology:**

   Describes the techniques and procedures used to identify and analyze information which is the CRoss Industry Standard Process for Data Mining (CRISP-DM), which consists of six steps explained in detail.

4. **Chapter 4: Results Analysis:**

   delves into the findings of this research along with detailed analysis.

5. **Chapter 5: Discussion:**

   Offers interpretations of the finding and recommendations for future research along with limitations and significance.

6. **Chapter 6: Conclusion:**

   Includes a brief restatement of the other chapters in this dissertation.

Chapter 2: Literature Review

This chapter presents a systematic review of literature on the integration of xAPI and AI in educational contexts.

Presenting the following:

- Overview
- Background.
- Search Method.
- Results and Discussion.
- Summary.

2.1 Overview

Utilizing xAPI and AI in educational settings is crucial for enhancing personalized learning experiences. xAPI allows for comprehensive tracking of diverse and detailed learner interactions, providing a rich dataset beyond conventional methods. AI’s predictive analytics can forecast students' performance, identify areas of struggle early, and facilitate timely intervention. This synergy between xAPI's data capturing capabilities and AI's analytical power can transform educational practices, making them more adaptive, efficient, and learner-centric, aligning with modern educational goals of personalization and effectiveness.

This chapter aims to investigates previous literature on the use AI-driven analysis of xAPI data stream in educational contexts.More specifically, attempting to provide a systematic

review of literature on the current state of xAPI-related research and provide nuanced input. Theis chapter proposes the following questions for this investigation:

1. Who are the targeted groups by the studies?
2. How AI technologies were used in conjunction with xAPI
3. What flavor of xAPI was used?
4. How does the current solutions compare to the recommended solutions?
5. What are the outcomes of those studies?

These questions, structured according to the PICO framework, can help in systematically analyzing the integration of xAPI and AI in various educational contexts, focusing on specific populations, interventions, comparisons, and outcomes.

2.2 Background

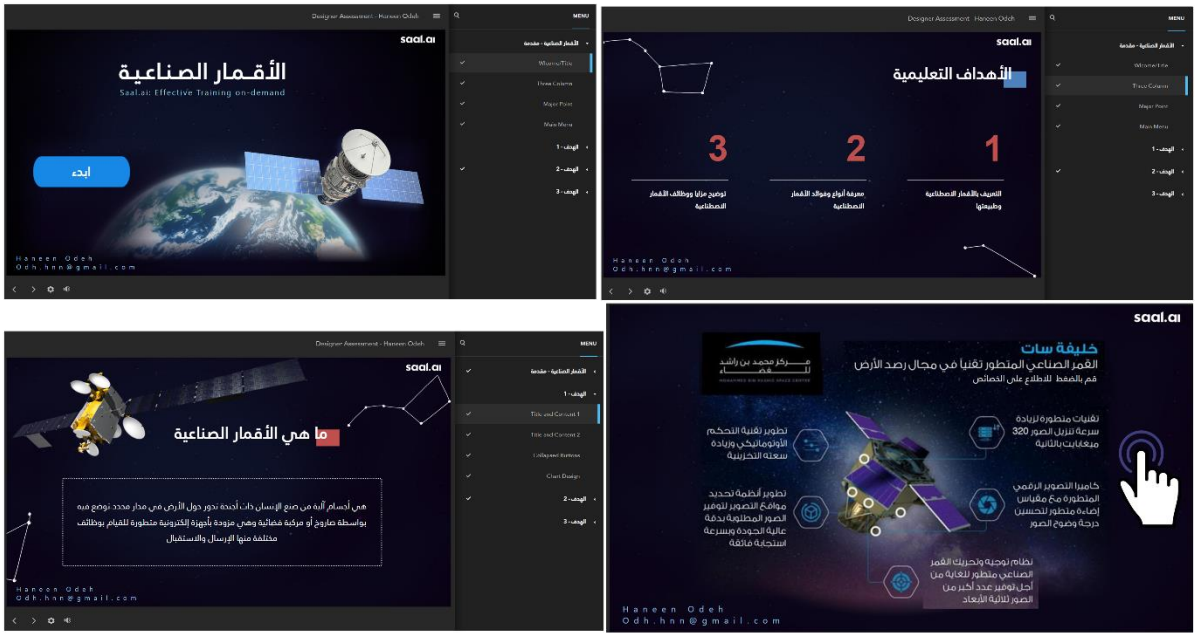
This section presents an overview and background on some key terminologies.

2.2.1 Interactive E-learning Lessons

E-learning lessons are web-based interactive slides. They gained popularity as replacement of PowerPoint slides in online learning. They can be accessed in a web browser without the need of any other software installations. They can also incorporate content, activities, videos, virtual tours, games, and much more, all within the same lesson package. Additionally, they capture student activity using xAPI. These types of lessons can be hosted online or within a learning management system (Yurtkan et al., 2023). Figure 1 showcases screenshots of an e-learning lesson.

Figure 1

Screenshots of An Interactive Lesson



2.2.2 Experience API

Experience API, (initially known as Tin Can API). It is a technical specification for the Learning and Development (L&D) industry used in e-learning lessons. It encodes learner's performance using a standardized format, following certain exchange rules to move those data to a data store or between applications (Heinemann et al., 2022).

xAPI can be implemented in any digital environment, including mobile learning, simulations, virtual worlds, serious games, interactive lessons...etc. It can be used to track and store data on any imaginable activity. Interactive e-learning web-based lessons are becoming more and more popular (Liu & Yu, 2023). xAPI capabilities enable these types of lessons to provide valuable insights. The xAPI standard also includes specifications for its use (xAPI

Profiles) as well as guidelines for how data is formatted, stored, and user authentication and access (Learning Record Stores) to record student activity in the form of xAPI statements.

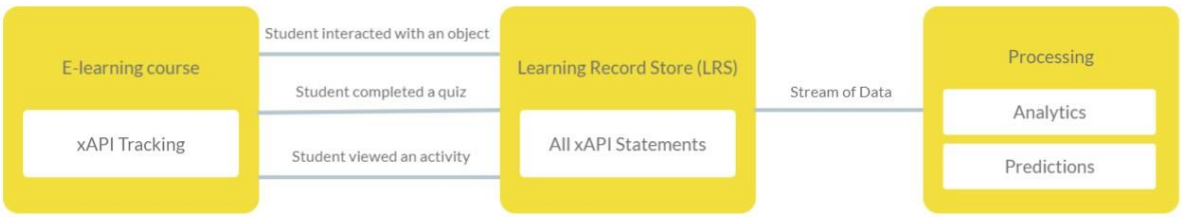
Figure 2

Components of an xAPI Statement

Figure 2 showcases the basic components an xAPI statement. xAPI statements are the basic building blocks of xAPI, they are triggered at each designated interaction between the learner and the e-learning content and contains information about the doer (actor) of an action, the action itself and the targeted learning object, additionally it contains optional information about the results, context, and the timestamp.

Figure 3

The General Workflow of Data



These statements are stored in Learning Record Store (LRS).In most cases, Learning and Development specialists interpret the stream of the data in the LRS or evaluate the generated graphs (Heinemann et al., 2022).

The workflow is summarized by Figure 3 .

2.2.3 Electronic Learning Standards

E-Learning standards includes the technical Specification that lays out a structure that describes how e-learning resources are built. A profile is a set of guidelines and specifications for implementing xAPI in a specific context. They provide a collection of statement templates, patterns, and particular vocabulary of terms and variable formats. xAPI Profiles help create semantic interoperability (Heinemann et al., 2022).

The three most commonly used e-learning standards are the xAPI, SCORM , and the cmi5 specifications (a flavor of the xAPI standard). The following table compares the three standards (Rustici Software, n.d.).

Table 1

Differences Between SCORM, xAPI and cmi5

	SCORM	xAPI	cmi5	Description
Defined content launch	Yes	no	Yes	instructions for content launch.
Track "anything"	no	Yes	Yes	allow for developer-defined data elements.
Normalized reporting	Yes	no	Yes	Rules for session identifiers so that statements can be grouped for normalized reports.
Mobile applications	no	Yes	Yes	track mobile applications.
Distributed content	no	Yes	Yes	content does not need to reside on the same server or domain as the LMS. Content can be located anywhere.
Data portability	no	Yes	Yes	data can be shared across systems.
Extensibility	no	Yes	Yes	Any learning data can be captured. The LMS uses LRS. With an LRS, a learning ecosystem beyond the LMS can easilyconnect to other systems.
Normalized completion criteria	Yes	no	Yes	rules for determining completion/mastery of learning activities.
Multiple lesson support	Yes	no	Yes	multiple objects in a defined hierarchy with criteria for progression.

Throughout the learning experience the learning environment fires statements as per profile standards, consisting mainly of actors (learners), verbs (actions defined by the profile), and objects (also defined by the learning profile). for example the following Table 2, lists verbs and activity types used by the xAPI and cmi5 profiles (Rustici Software, n.d.).

Table 2

Overview of the Most Popular Profiles

	xAPI	cmi5	
Verbs	answered, asked, attempted, attended, commented, exited, experienced, imported, interacted, launched, mastered, preferred, progressed, registered, shared, voided,logged-in, logged-out	Launched, Terminated, Completed, Abandoned, Satisfied	Initialized, Passed, Failed, Waived,
Activity Types	file, link, media, meeting, performance, question, simulation	course, block	

2.2.4 Adaptive Learning

Adaptive learning is a learning style in which the needs of each individual learner is addressed through learning pathways, effective feedback, and supplemental resources; as opposed to an one-size-fits-all linear path of learning (Plass & Pawar, 2020).

Table 3

Summary of Adaptive Learning Models

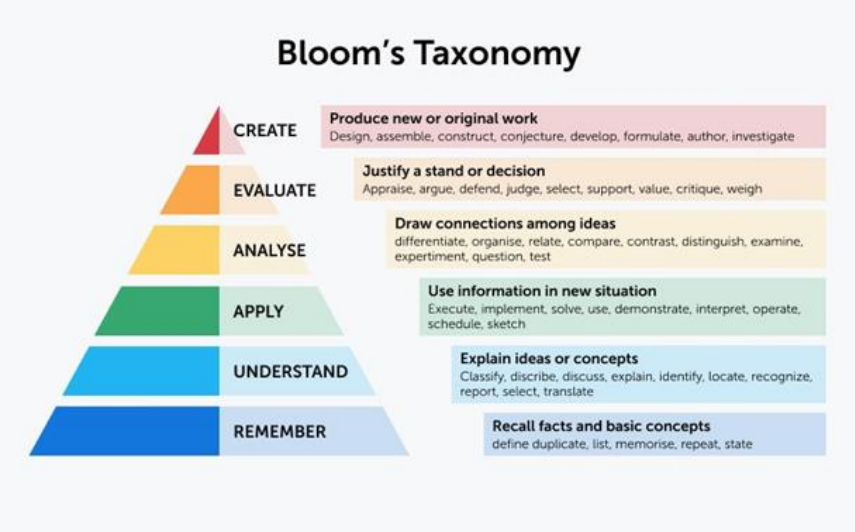
Model	Description
Student Model	Represents individual learners and their characteristics, such as knowledge, skills, preferences, and learning progress. It is contenuously updated to provide personalized learning experiences.
Instructional Model	Defines how content is delivered to learners, including strategies for presenting material, sequencing activities, and assessingprogress. It adapts content and activities to match the learner's profile and learning objectives.
Expert Model	Represents domain-specific knowledge or expertise related to the subject matter being taught. It includes information, rules, and relationships relevant to the topic and guides content creation and assessment design.
Instructional Environment	Refers to the digital platform or system where adaptive learning occurs. It encompasses the user interface, interactive elements, feedback mechanisms, and communication tools. The instructional environment is essential for delivering personalized learning experiences.

2.2.5 Blooms Taxonomy

Bloom's taxonomy is a hierarchical model used to classify educational learning objectives into levels of complexity and specificity. It provides educators with a framework to structure their teaching and assessment methods. The taxonomy consists of six levels: Remember, Understand, Apply, Analyze, Evaluate, Create. Each level represents a different type of cognitive skill, starting from basic recall of facts to higher-order thinking skills like evaluation and creation(Anderson & Krathwohl, 2001).

Figure 4

Revised Blooms Taxonomy



This taxonomy is widely used by educators, especially when crafting learning objectives. Each layer of the hierarchy is associated with certain verbs and actions indicating the comprehension stage of the learners (Santamaría-Bonfil et al., 2019). Figure 4 describes the taxonomy.

2.3 Search Method

The purpose of this literature review is to comprehensively analyze and synthesize the existing body of research. The review aims to provide an overview of the current state of knowledge, identify key trends and developments and highlight gaps or areas requiring further investigation.

2.3.1 Databases and Sources

Scopus and IEEXplore, emerald, and ACM Digital libraries are included, they allow search results to be exported to simplify the filtering process. Additionally, relevant google scholar search results, industry reports, and institutional websites will be explored to gather a diverse range of sources.

2.3.2 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria at listed in the table below:

Table 4

Inclusion and Exclusion Criteria

Exclusion Criteria	Inclusion Criteria
Relevance: Publications not related to xAPI data processing	Publication Date: Publications from 2018 to 2023.
Quality Assessment: Publications failing quality measures	Publication Type: Journal articles.

Length: Publications with fewer than 5 pages. Journal rating is not Q1 or Q2	Length: Publications with more than 5 pages. Language: English. Accessibility: Available through the chosen academic sources

2.3.3 Keywords and Search Strategy

The following keywords and search terms will be employed to identify relevant literature:

- "xAPI" OR "Experience API" OR "Tin Can API"
- "cmi5"

The combination of these terms will be used to retrieve records from the selected databases and those results will go through the filtering process. The results exported after applying the available inclusion/exclusion criteria filters are listed in the table below:

Table 5

Total Number of Articles Before Removing the Duplicates

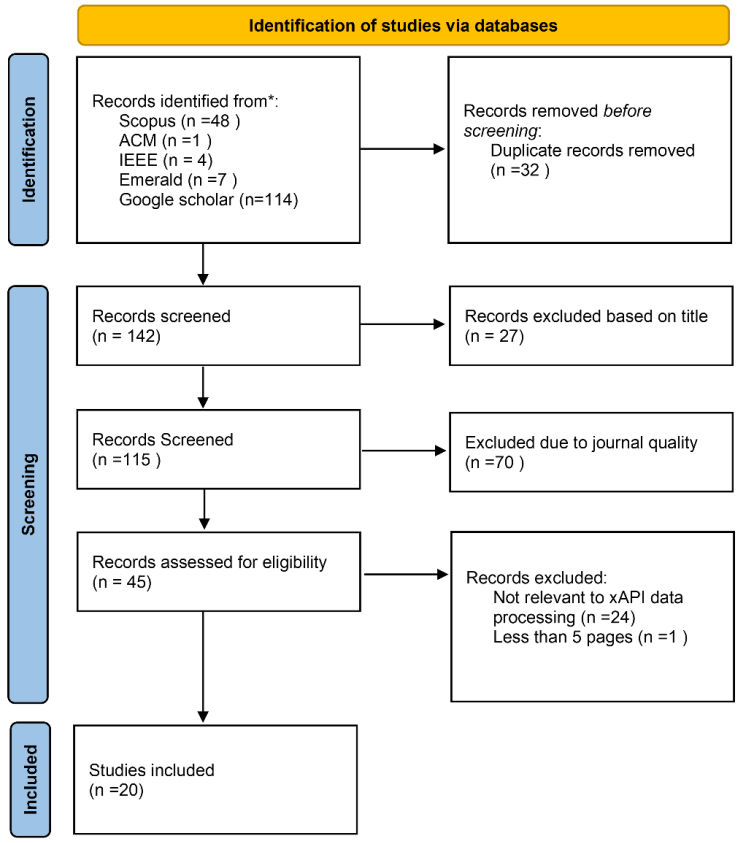
Database	Count
Scopus	48
ACM	1
IEEE	4
Emerald	7
Google Scholar	114
Total	174

Farther refinement of the results took place in order to meet the exclusion and inclusion criteria. Figure 5 showcases the PRISMA flowchart that illustrates the refinement process.

The initial search yielded a total of 174 records, it's worth mentioning that google scholar search resulted in 21 records including the "cmi5" term and zero was the result from other databases. Which indicates a gap in research. After 32 duplicated were removed, screening for the inclusion and exclusion criteria listed in Table 4 took place, resulting in 20 records remaining for this review.

Figure 5

The PRISMA Flowchart



Details about the selected papers can be found in the Table 12.

2.3.4 Quality Assessment

The quality assessment checklist is created to farther evaluate the selected papers. It consists of a list of questions as shown in Table 6. Each study will answer to those question in accordance with a three-point system, where "1" indicates a yes, and "0" indicates a no, and "0.5" means partial satisfaction. Meaning that the maximum score a study can get is 7.

Table 6

Quality Assessment Checklist

	Question
Q1	Are the research aims clearly specified?
Q2	Does the study provide contributions to xAPI specifications?
Q3	Does the study integrate AI and machine learning techniques?
Q4	Were the outcomes clearly explained?
Q5	Does the study use comprehensive datasets?
Q6	Does the study provide interpretation of xAPI data?
Q7	Does the study mention the targeted demographic?

Table 7

Quality Assessment Results

Table 7 shows the results of the quality assessment. If a study exceeds 50% score, it is then accepted. All 20 studies have passed the quality assessment.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	TOT
S1	1	1	1	1	1	1	1	7
S2	1	0	1	1	0.5	1	1	5.5
S3	1	0	0	1	1	1	1	5
S4	1	0	0	1	1	1	1	5
S5	1	0	0	1	1	1	1	5
S6	1	1	0	1	1	1	1	6
S7	1	0.5	0	1	1	1	1	5.5
S8	1	1	0	1	1	1	1	6
S9	1	1	0	1	1	1	1	6
S10	1	0	1	1	1	1	1	6
S11	1	0	0	1	1	1	1	5
S12	1	1	0	1	0	1	1	5
S13	1	0	0	1	1	1	1	5
S14	1	0	0	1	1	1	1	5
S15	1	0	0	1	1	1	1	5
S16	1	0	1	1	1	1	1	6
S17	1	0	0	1	1	1	1	5

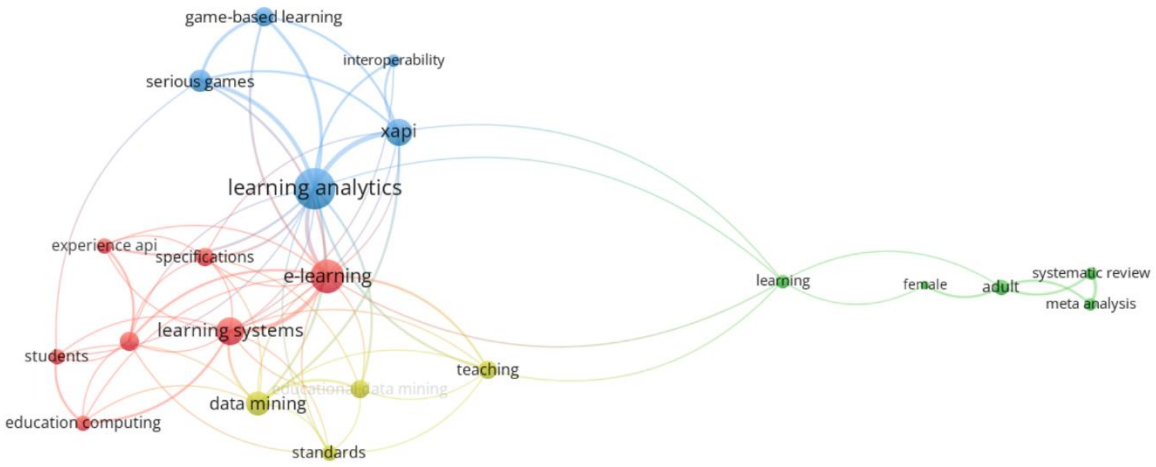
S18	1	0	0	1	1	1	1	5
S19	1	0	1	1	1	1	1	6
S20	1	0	0	1	1	1	1	5

2.4 Results and Discussion

In this section, the literature review questions will be answered based on the studies selected. Figure 6 illustrates the results of keyword analysis of the queried studies, themes of serious games, learning analytics are dominant for the most part.

Figure 6

VOS Viewer Results of Queried Studies



2.4.1 Q1: Who are the targeted groups by the studies?

Figure 7

Targeted Demographics by the Studies

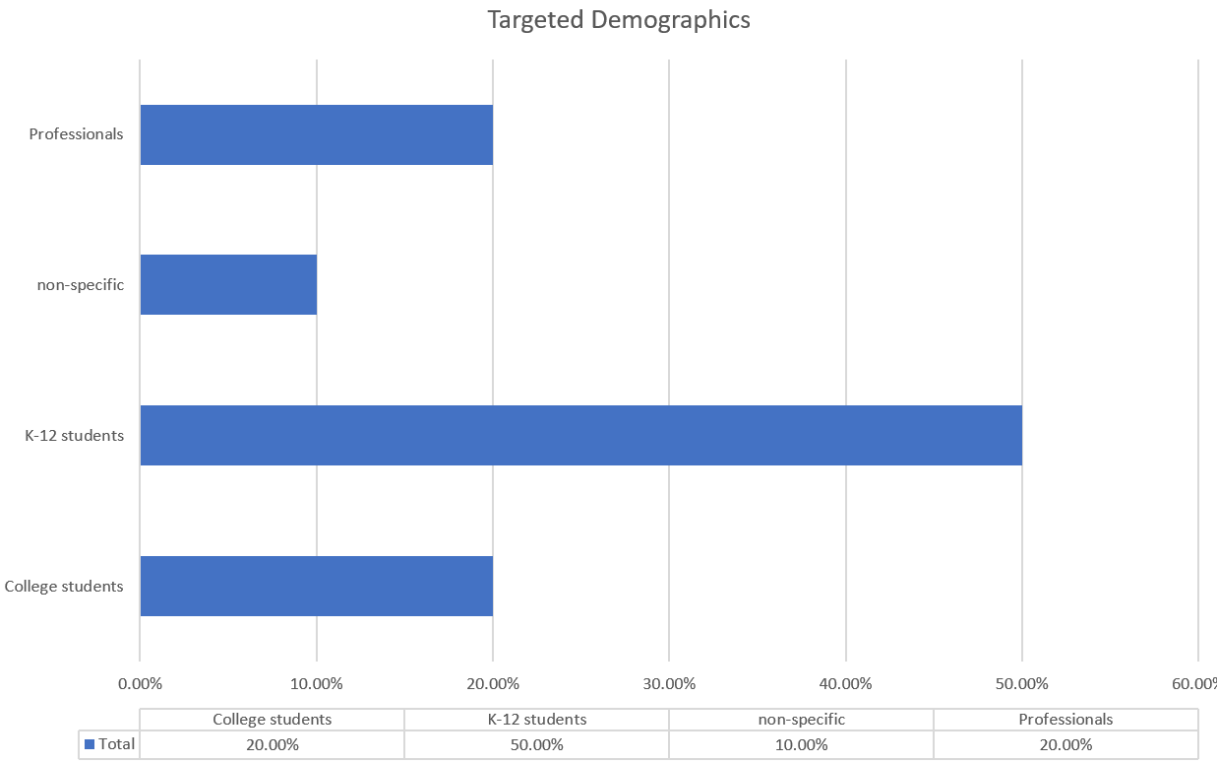


Figure 7 showcases the targeted groups of learners. We conclude that there is a variety of xAPI applications for all types of learners and industries.

For example, (Yurtkan et al., 2023) and (Mohammad et al., 2023) used the same xAPI dataset for school students. The dataset contains 16 features were some are behavioral, and the rest are student profile attributes such as grade level and section. Which makes this application specific to school students. Others like (Calvo-Morata et al., 2019), (Alonso-Fernández et al., 2023), and (Alonso-Fernández et al., 2020) targeted students and used gaming analytics features, which is also applicable to other types of learners.

20% of the studies took place in higher education institutions for various applications. Such as assessment tracking (Nouira et al., 2019), gamification (Shum et al., 2023), online laboratories (Ruano et al., 2023), and improve usability of current systems (Chen & Chang, 2019).

xAPI has shown usefulness in training professionals and public education as well. for example (Santamaría-Bonfil et al., 2019) tracked data from simulation training for linemen. (Cano et al., 2018) analyzed data from a learning game for adults with intellectual disabilities. In the medical field, (Durojaiye et al., 2018) created dashboards analyzing residents assessments and interactions.

2.4.2 Q2: How were AI Technologies Used in Conjunction with xAPI?

Figure 8

Studies that Utilized ML

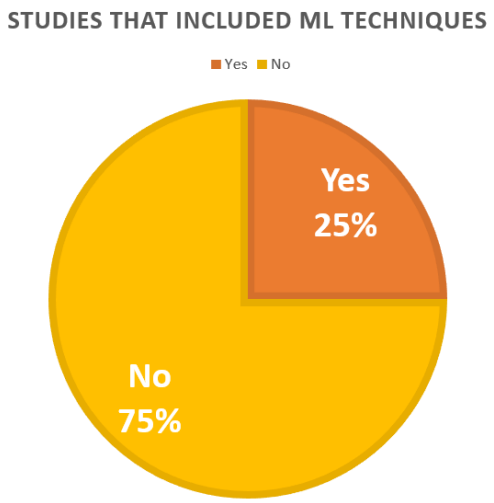


Figure 8 indicates that only 25% of the studies utilized ML techniques. One study collects xAPI data from simulations and trainees self-report their emotional state. Clustering

algorithms (Hierarchical Agglomerative Clustering (HAC), the DIvisive ANAlysis Clustering (DIANA), K-Means, and Partition Around Medoids (PAM)) are then employed to select learning paths (Santamaría-Bonfil et al., 2019).

The rest of the studies used prediction models. Gamification in e-learning applications utilized data obtained from the experience API serious games profile (xAPI-SG) in two studies. One study (Alonso-Fernández et al., 2020) implemented Two types of models were created: linear models to predict exact score in range (0–15), and the different classification models to predict pass/fail category and yielded results with high accuracy based on a post-test. The other study (Alonso-Fernández et al., 2023) used nine predication models (Linear regression, Regression trees, Bayesian ridge regression, SVR, kNN, Neural Networks, Random Forests, Adaboost, Gradient boosting). All models yielded acceptable results, the top performing models is a Bayesian regression, followed by a gradient boosting model.

Two studies used the same xAPI dataset from Kaggle to draw predictions. The dataset contains 16 features and 480 records. Figure 9 shows the 16 attributes in this dataset. Prediction Using Feedforward Neural Networks yielded and accuracy of 91.95% (exact + one grade difference accuracy) (Yurtkan et al., 2023). The CNN approach gave higher accuracy than all other traditional machine learning classifiers tested, yielding an accuracy of 98.57% (Mohammad et al., 2023)

Figure 9

Kaggle's xAPI Dataset Attributes

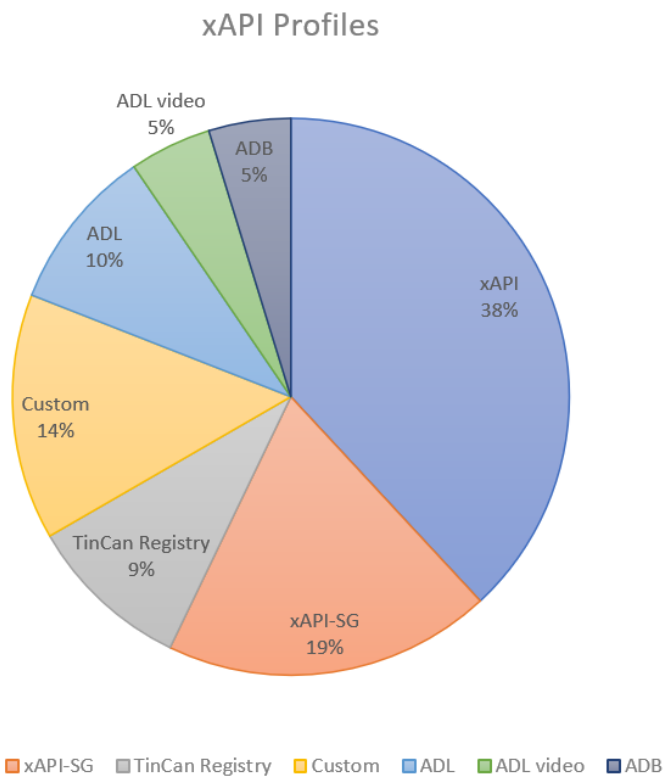
	0	1	2	3	4	5	6	7
gender		F	M					
NationalITy		Egypt	Iran	Iraq	Jordan	KW	lebanon	Lybia
PlaceofBirth		Egypt	Iran	Iraq	Jordan	KuwaIT	lebanon	Lybia
StageID		lowerlevel	HighSchoc	MiddleSchool				
GradeID		G-02	G-04	G-05	G-06	G-07	G-08	G-09
SectionID		A	B	C				
Topic		Arabic	Biology	Chemistry	English	French	Geology	History
Semester		F	S					
Relation		Father	Mum					
raisedhands								
VisITedResources								
AnnouncementsView								
Discussion								
ParentAnsweringSur		No	Yes					
ParentschoolSatisfac		Bad	Good					
StudentAbsenceDays		Above-7	Under-7					
Class		H	L	M				

It's important to note that while the integration of AI technologies with xAPI is evident in these papers, some papers did not incorporate AI and relied solely on xAPI data for analysis. Overall, the integration of AI technologies with xAPI appears to be a growing trend in the field of educational research, with the aim of enhancing learning analytics, personalizing learning experiences, and predicting student outcomes. However, the extent and sophistication of AI integration can vary from one study to another.

2.4.3 Q3: What flavor of xAPI was used?

Figure 10

Xapi Profiles Used



The findings from the selected literature review reveal that a diverse range of xAPI specifications and configurations were utilized across the examined papers for data collection. While 35% papers employed plain xAPI profiles, other integrated xAPI-SG (Serious Games) to assess user interactions within educational games. Additionally, the use of TinCan's registry extensions and ADL (Advanced Distributed Learning) was observed in certain studies. These findings underscore the versatility of xAPI in capturing and analyzing data related to learning and performance across various educational contexts, with approximately 86% of the studies

using predefined profiles, a minority of 14% utilizing custom profiles or based on the xAPI configurations.

2.4.4 Q4: How does the Current Solutions Compare to the Recommended Solutions?

All 100% used interaction-centric profile properties which caused issues with the semantic understanding of learning outcomes. We recommend that at the data collection stage use a custom xAPI tailored to track learning outcomes progression based on cmi5 standards that has better defined hierarchies. Instead, studies sought complex ontology-based approaches (Nouira et al., 2019; Vidal et al., 2018).

Overall, this demonstrates xAPI's potential for enhancing educational research and analytics and, it's limitations. One of the key limitations is the lack of standardization in how xAPI data is structured and collected across different applications and systems. This can lead to challenges in data integration and interoperability, as xAPI statements from various sources may not be directly compatible. So, it is recommended to use basic structures.

Additionally, xAPI does not inherently support certain features, such as content sequencing and navigation. While these features can be implemented using xAPI, it often requires additional development effort. Sequencing can be tracked using the timestamps and is handled by the LRS, in the proposed solution each interaction is tagged by its corresponding learning objective.

Many studies focused on creating effective and easy to understand dashboards, these dashboards can be overwhelming for learners and educators, the use of OpenAI's chatGPT's API to interpret data can help provide instant feedback and provide a more a human-friendly experience.

2.4.5 Q5: What are the Outcomes of those Studies?

In the reviewed studies, various contributions and conclusions were observed. (Santamaría-Bonfil et al., 2019) contributed by collecting xAPI data from simulations and trainees' self-reports of emotional states, utilizing clustering algorithms to select learning paths, and presenting a framework to collect data from non-xAPI compliant means. The results show that capturing the semantic meaning of description texts could improve the selection of learning paths.

Yurtkan et al. (Yurtkan et al., 2023) focused on predicting student success using Feedforward Neural Networks and xAPI data, concluding that behavioral data is a more indicative predictor of student performance.

Multiple studies focused on creating analytical dashboards. Their conclusion emphasized the value these dashboards brought to teachers (Calvo-Morata et al., 2019) .highlighting xAPI's suitability for handling low-level microtransactions (del Molino et al., 2020). These dashboards understand user perception on a digital humanities research platform, benefiting usability improvements (Chen & Chang, 2019).

Nouira et al. (Nouira et al., 2019) and Vidal et al. (Vidal et al., 2018) developed an ontology-based framework to interpret xAPI data, concluding that ontologies can help classify the real level of learners based on assessment performance but . The results show compliance with most of the standard but partial support for the activities model. This showcases the standardization issues with the data collection.

Wu et al. (2020) (Wu et al., 2020) designed a data collection mechanism for 3D design courses based on a custom xAPI standard, concluding that xAPI can track mouse and keyboard movements and students' learning paths.

2.5 Summary

The reviewed papers demonstrate that xAPI has been applied across a wide spectrum of educational settings, from linemen training to STEM education. It is a versatile technology that can be adapted to capture and analyze learning interactions in different domains.

Several studies explore the use of xAPI data in predictive analytics, particularly in predicting student performance. Behavioral data often proves to be more indicative of student outcomes than static attributes, underscoring the value of continuous data collection.

Some papers propose ontology-based frameworks to enhance the classification and semantic understanding of xAPI data, especially in assessment contexts. These frameworks aim to improve the quality of data interpretation.

Gamification, supported by xAPI, has been effective in enhancing student engagement and improving the learning experience in various educational contexts. The serious games profile xAPI-SG has been widely used for those use cases. However, some developed dedicated custom profile to accommodate 3d interactions and spatial awareness.

The review also acknowledges challenges, for example when selecting a learning path, some studies resorted to ontology-based approaches and others recommended semantic parsing of descriptor texts. These issues arise due to the fact that most xAPI profiles identify interactions with objects on the screen and are not pedagogy related, which makes it more difficult to interpret student understanding. We recommend for future work to design a

pedagogy-centric xAPI standard to provide learning-related features and information on the cognitive state of the learners.

Furthermore, a minority of the selected studies have explored the use machine learning methodologies with xAPI data. Predication of student performance was the most sought-after ML task in the studies. Furthermore, most of the studies did not provide details on their datasets features and types of data extracted and only mentions the xAPI profile, which indicates types of interactions captured by the system.

In summary, the systematic review of these selected papers has shed light on the multifaceted applications of xAPI in education and learning analytics. It underscores the importance of continuous data collection, personalized learning, and the potential of xAPI to revolutionize how we understand and support learning processes. However, ongoing research and innovation are essential to harness the full potential of xAPI and address the challenges it presents in educational contexts.

Chapter 3: Methodology

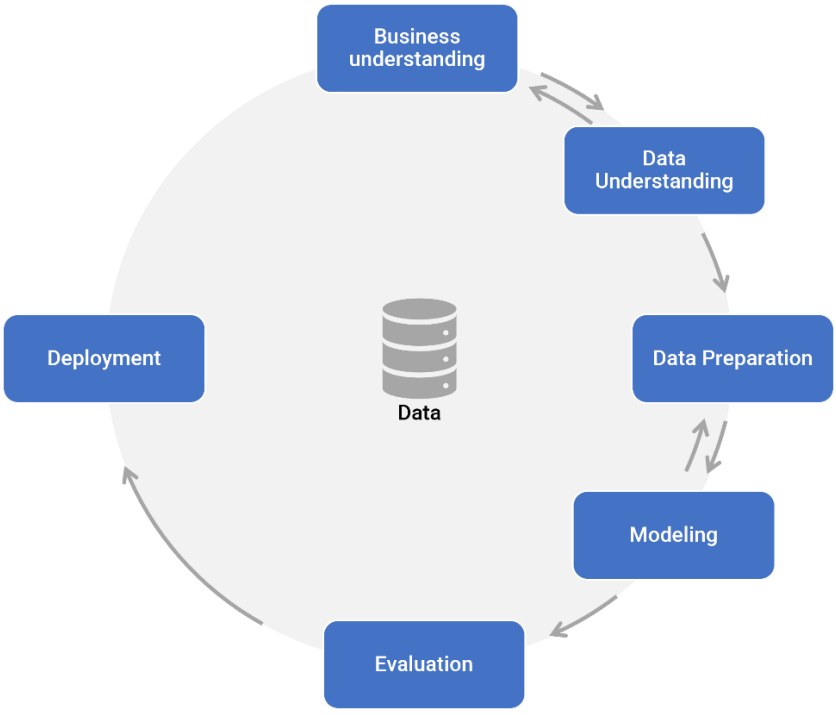
The purpose of this dissertation is to predict students' outcomes based on the xAPI data produced by an elearning interactive lesson.

This chapter aims to describe the research methodology of this study, which is based on the The CRoss Industry Standard Process for Data Mining (CRISP-DM) (Schröer et al., 2021)

As the name suggests, the CRISP-DM is widely used across all types of industries to guide the data mining efforts. It consists of six iterative phases showcased in Figure 11.

Figure 11

The CRISP-DM Workflow



3.1 Business Understanding

In this initial phase, the primary focus is on understanding the objectives and requirements. This step involves defining the problem, establishing goals, and understanding how data mining and machine learning can provide value.

3.1.1 Background and Context

The first phase of our research is focused on achieving a profound understanding of the e-learning technologies. We aim to comprehend the nuances of our problem, which revolves around enhancing personalized learning experiences through AI-driven analysis of xAPI data. To achieve this, a comprehensive review of literature provided an overview of the current landscape. It was concluded that xAPI technologies haven't been utilized widely and there was a dependence on PowerPoint slides to provide content to the students, which aren't as responsive and do not provide enough information on the student experience. Using xAPI-supported learning materials will help educators make more informed decisions to adapt content and provide needed support. Machine learning predictions can guide those interventions to support student needs. Also, in scenarios were xAPI analytics were implements it was utilized to create dashboard and the process of adopting these dashboards was met with challenges due to their complexity and the overwhelming amount of information presented to educators. The data is better used in a synthesized human-friendly manner, using AI technology to interpret data and provide custom feedback to the students can lift the weight of monitoring each and every student.

3.1.2 Ethical Considerations

Research involving AI-driven analysis of xAPI data in the context of enhancing personalized learning experiences raises several ethical considerations that should be carefully addressed throughout the research process.

Students' data privacy is of utmost importance. So, a clear of data collection, storage, and usage will be included in the ethical research form and to the learners. The data will be anonymized since no private or personal data will be used aside from gender and age, and those data is not stored longer than necessary for research purposes.

Ethical approval and oversight from the relevant ethics committee to ensure that the research complies with ethical standards and regulations. Research complies with all applicable laws and regulations related to data privacy, security, and research ethics.

3.1.3 Objectives

This study uses data obtained from student interactions with learning materials and machine learning tools to build a predictive model for student performance to enhance personalized learning.

So, what is needed to be done is to create a framework in which we can track of student cognitive competency and predict the areas of struggle and then provide custom recommendations to them to pinpoint areas they need to work on and measures they can take to improve their performance. In order to achieve this, we must define xAPI attributes and design the model of communication between all the elements of this pipeline.

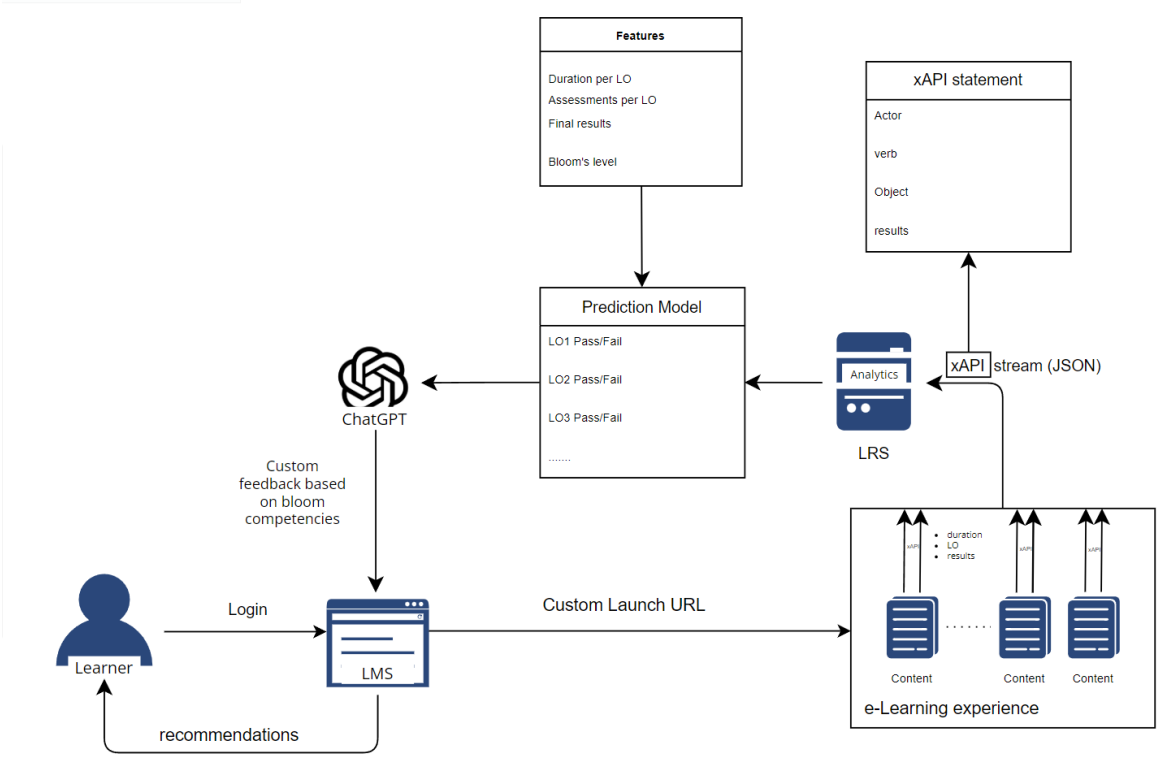
3.1.4 Data Flow

Typically, student's login to a learning management system using their credentials. Once authorized and identified, they can gain access to their courses. When a student launches a course, a custom URL is built to initiate an attempt at a learning content which can be anything from videos, slides, simulations ...etc. This URL supplies information about the xAPI actor and the destination LRS. The learning content uses this information to send a stream of xAPI statements detailing learners' interactions. These statements consist of six different parts. The actor field identifies the student, while the verb explains what they did, the object identifies what part of the experience the actor interacted with. Lastly the result provides score, response, and duration of the interaction. The Learning Record Store (LRS) contains all the statements produced by the learners, it also provides dashboards and data analytics. Some learning management systems support xAPI and integrate LRS within their system. Otherwise, a standalone LRS is available for use. This was the typical flow of data for the majority of xAPI application.

As for the contribution of this paper, we attach learning objective and bloom level information to the xAPI data. Additionally, a classification prediction model will predict if a student might pass or fail a learning objective based on the bloom competency level and then using ChatGPT provide suitable recommendation in text format. This updated data flow is illustrated in Figure 12 below.

Figure 12

The Flow of Data



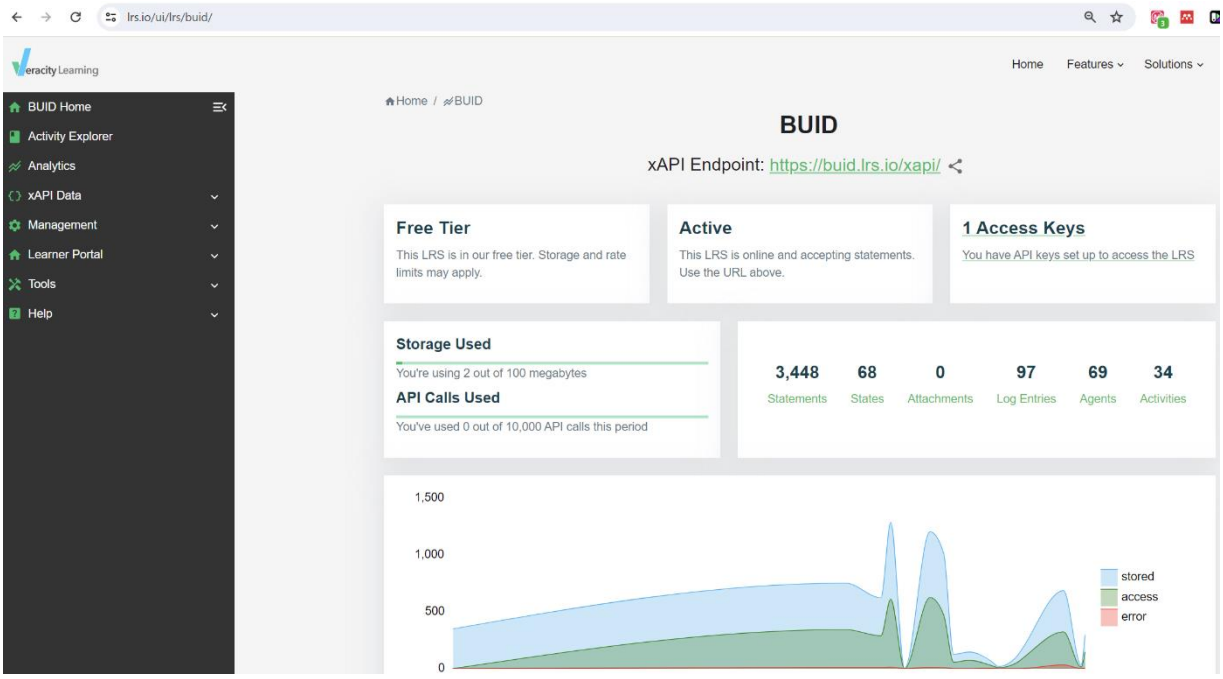
3.1.5 Data Flow Design

The scope of this study is to investigate on a smaller scale the feasibility of the framework. So, the data design takes into consideration the scalability of this model.

3.1.5.1 Step1: the LRS Involves setting up a Learning Record Store (LRS) using LRS.io. This step is crucial because an LRS is a specialized server for storing and retrieving records in xAPI format. These records are known as statements, and they describe a learner's activities. The LRS from LRS.io functions as a central repository for all the learning data collected via xAPI. It's designed to receive, store, and return data about learners and their activities. A key aspect of this step is ensuring that the LRS is correctly configured to interact with eLearning content and record the necessary data. This setup is essential for tracking, analyzing, and reporting learning experiences, as well as for integrating with other systems if needed. This involves creating access keys and assigning privileges.

Figure 13

The LRS UI



Two LRS servers were created, one for initial testing and the other for deployment. The purpose of the initial testing server is to load sample data and create custom dashboards using

the Veracity Query Language (VQL), and to test the lesson and xAPI before initializing the data collection phase.

3.1.5.2 Step2: xAPI Design The focus is on creating the xAPI (Experience API) profile tailored to this study's needs. xAPI is a standard for data collection that enables the tracking of learning experiences. This step involves defining the specific types of learner activities and interactions to track. For each activity, it is crucial to build the xAPI statements' structure, including the actor (learner), verb (action taken), object (item interacted with), and other relevant data points. The design must be comprehensive enough to capture detailed and meaningful data while being compatible with the overall technological infrastructure of the basic LMS, LRS and the eLearning environment. Below is a code snippet from a statement in the raw JSON format.


```
{
  "id": "745b2952-8d9b-4c05-803e-16fb2cffff8f",
  "timestamp": "2024-03-12T15:15:54.480Z",
  "actor": {
    "objectType": "Agent",
    "mbox": "mailto:UFsdGVkXXRnbeCYCBdzylEZvtaATnpuqpXKk@yahoo.com",
    "name": "UFsdGVkXdaGHJSvEJJTucGImHJGOWqjNZUusoNFyWsxlAnkllS"
  },
  "verb": {
    "id": "http://adlnet.gov/expapi/verbs/passed",
    "display": {
      "en-US": "Passed"
    }
```

```
  },
  "result": {
    "success": true,
    "duration": "PT26.304S",
    "response": "Abstract[,]Introduction[,]Literature
Review[,]Methodology[,]Findings[,]Analysis & Discussion[,]Conclusion",
    "score": {
      "raw": 10,
      "max": 10
    }
  },
  "object": {
    "id": "urn:articulate:storyline:ResearchBUID/5jld8lSzLJh",
    "objectType": "Activity",
    "definition": {
      "type": "http://adlnet.gov/expapi/activities/cmi.interaction",
      "name": {
        "en-US": "Pre2-Key Components of a research paper"
      },
      "interactionType": "sequencing",
      "correctResponsesPattern": [
        "Abstract[,]Introduction[,]Literature
Review[,]Methodology[,]Findings[,]Analysis & Discussion[,]Conclusion"
      ],
      "extensions": {
```

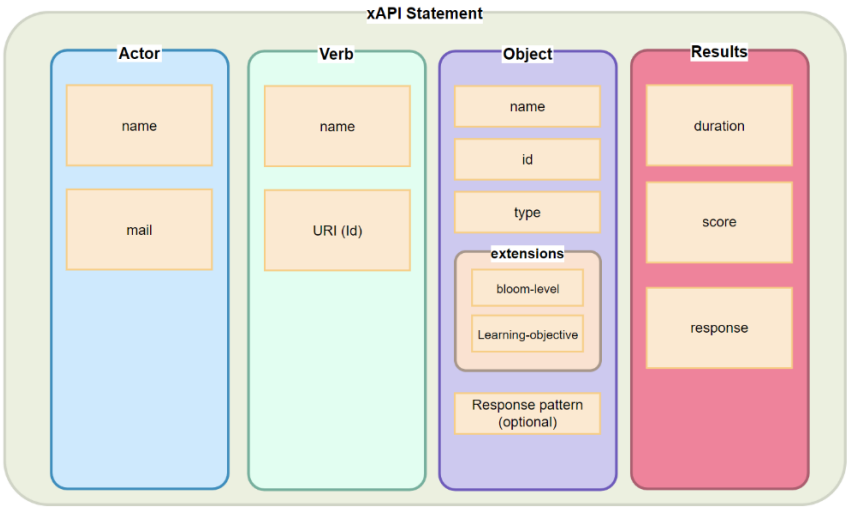
```
        "learning-objective": "LO2:List the key components of a research
paper.",
        "blooms-level": "2"
      },
      ...
    }
  }
  }
```


In this study the xAPI data stream needs to send bloom taxonomy level and learning objective associated which will be attached to the object as extension. The profile must include all the other standard specifications. Each xAPI statement triggered will also contain information about progress relevant to associated learning objective as a result block. The building blocks of the xAPI profile are shown in

below.

Figure 14

The Breakdown of an xAPI Statement



To keep it simple and scalable we will define few verbs, listed in Table 7. Additionally, we also need to define object types which can be seen in Table 9. The extensions added to the object are also defined in Table 10.

Table 8

Profile Verbs

Verb	Description
completed	Indicates the actor finished or concluded the course.
attempted	Indicates the actor attempted to start a course.
Experienced	Indicates the actor experienced an object.
left	Indicates the actor left an object.
Answered	Indicates that the actor answered a query question.
failed	Indicates the actor did not successfully pass an activity to a level of predetermined satisfaction
Passed	Indicates the actor did successfully pass an activity to a level of predetermined satisfaction

Table 9

Profile Object Types

Object	Description
course	Content to be completed. It is represented with a Course Structure Format.
Activity	We define three types of activities (sequencing, matching, choice) which result in a score, success, or failure. Type module contains only passive content.

Table 10

Profile Extensions

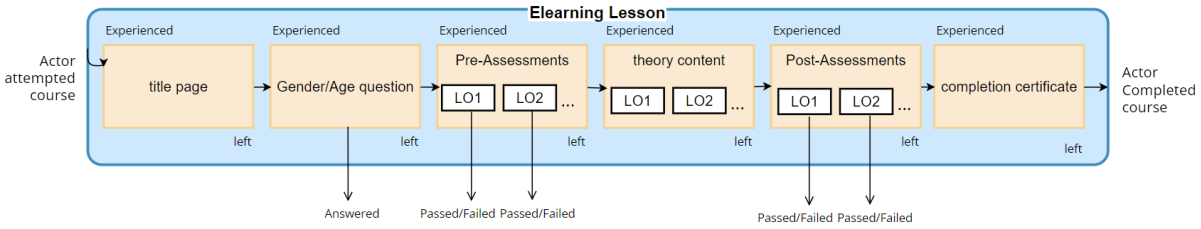
Name	Description	values
Learning outcome	Associated teaching point	string
Bloom level	Associated bloom level of the learning outcome	numbers from 1 to 6

3.1.5.3 Step3: E-Learning Lesson Implementation. Develop and integrate eLearning content that's compatible with xAPI. This involves creating or selecting educational materials and embedding xAPI code to track interactions. Each interaction or activity within the lesson is coded to send xAPI statements to the LRS. These statements are detailed logs of student activities, capturing who did what, and when. This setup ensures that learner engagement with the course material is systematically tracked and recorded, providing a rich dataset for later analysis. The design and implementation of the eLearning content should be thoughtfully aligned with the learning objectives and the data capture requirements defined in the xAPI design phase.

The lesson integrates both pre-assessment and post-assessment quizzes seamlessly into its structure. These assessments will serve as critical data sources, allowing the evaluation of student performance. One of the lessons is based on an introductory lecture on writing a research paper and will be assigned to university students online where we can obtain more information on the learner's attributes. The Figure 15 summarizes the design of the eLearning lesson. It is worth noting that the structure of this lesson can be applied to a variety of applications and eLearning scenarios. The statements experienced, left, attempted, and completed are already sent by default in most applications and by the majority of eLearning authoring tools. Some authoring tools opt for using the verb answered for assessments and attach pass/fail status in the results section while some send pass/fail as verbs in statements. Pass/Fail style was selected so we can have more of a standardized form for each verb since not everything being answered requires a score. The verb answered is used for those cases when a question doesn't require a score such as query questions.

Figure 15

Summary of Lesson Design



As for the topic of the lesson, it was adapted from a lecture "how to write a research paper" given by a university in the UAE. The targeted demographic is the general public. So, the lesson was made to be easy to follow along and provided basic understanding of the topic in hand. The lesson consists of three learning objectives, each learning objective is assigned a bloom level.

3.1.5.4 Step4: Login Page. A custom login page is created, serving as a gateway to the eLearning content and simulated and LMS behavior at launch. This page is crucial for two main purposes:

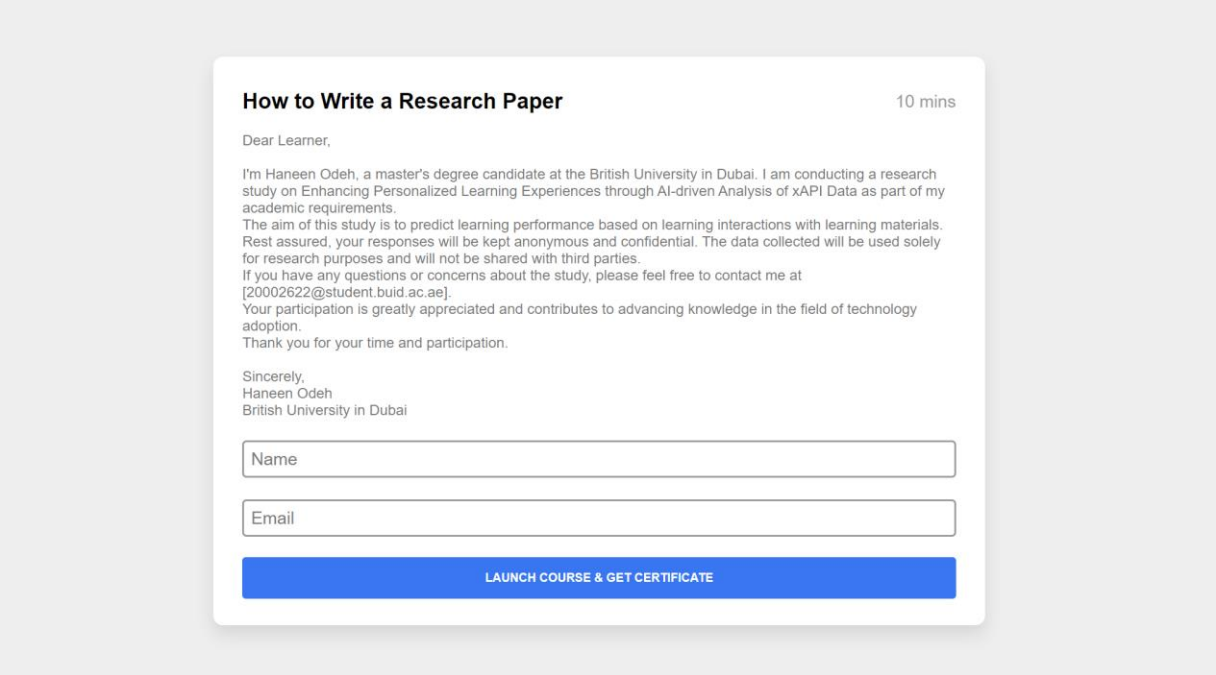
1. **Creating a Secure Launch URL:** When a user logs in, the system generates a unique launch URL. This URL contains encrypted user data, along with the endpoint and access key for the Learning Record Store (LRS). Encrypting this information ensures

secure communication between the eLearning content and the LRS, maintaining the integrity and privacy of user data.

2. **iFrame Loading and Session Management:** The eLearning lesson is loaded within an iframe on this page. This setup allows for a seamless integration of the lesson within the webpage. Additionally, the system is designed to request login credentials again upon page reload. This feature is essential for security and to prevent users from sharing their unique URL, as each session is tied to the individual user's login, ensuring that the tracked data accurately reflects each user's interactions with the lesson.

Figure 16

The Login Page UI



3.1.5.5 Step5: Hosting the Content. Hosting the eLearning lesson on Google Cloud. Google Cloud is chosen for its scalability, reliability, and security features. To do this, first created a Google Cloud Storage bucket. This bucket acts as a container for the lesson data, files, and related resources. After creating the bucket, the settings needed to be configured to ensure its publicly accessible over the internet. This involves setting appropriate permissions so that the eLearning content can be accessed by the intended users. The setup includes assigning a URL to the bucket for easy access and ensuring that the hosting environment aligns with the technical requirements of the eLearning lesson and the xAPI data tracking mechanism.

After the lesson passed the testing stage, the link was sent through the proper channels for approval. Once approved along with feedback, the student version is uploaded ready to be consumed.

3.1.5.6 Step6: Exporting Data. The LRS dashboards are farther tailored to provide meaningful insights into the learners' interactions with the eLearning content. This customization involves setting up visualizations and reports that can highlight key aspects of learner behavior. The aim is to make these insights actionable, helping to understand the effectiveness of the learning content and participants responses.

Once the dashboards are fine-tuned to present the required insights, the next step is to prepare the xAPI data for export. The data, which encapsulates detailed records of student interactions, in the raw JSON format.

3.1.5.7 Step7: Classification Model. The exported JSON data is now primed for use in the classification model after the data cleaning. This model will analyze the data to predict student pass/fail state which will help to identify learning patterns. The classification mode will utilize this dataset to draw insights and make predictions, feeding into the AI-driven personalized learning framework.

The features to be analyzed are duration per learning objective, pre-assessment scores per learning objectives, blooms level per learning objective and lastly gender and age information. The goal is to analyze which attributes contributes to better predictions. Some feature engineering will also take place to find the best possible combination of features.

The focus in developing a classification model is to learns from data, identifying patterns and correlations that can be used to make predictions about new data. Once the model is trained and its accuracy is validated, it serves as a powerful tool for providing insights into student learning processes and guiding the development of personalized educational strategies.

3.1.5.8 Step8: Personalized Feedback. The integration of ChatGPT plays a crucial role. After the classification model has predicted student outcomes and identified learning gaps, ChatGPT is used to provide personalized feedback and recommendations. Leveraging its natural language processing capabilities, ChatGPT analyzes the model's findings to generate contextually relevant and actionable advice for each student. This feedback is tailored to address specific areas where a student might need additional support or resources, aligning with the identified Bloom's competency levels. ChatGPT's ability to generate human-like text makes this feedback engaging and easy to understand, enhancing the overall learning experience

In this study, it's important to note that there isn't a Learning Management System (LMS) integrated for direct interaction with students. This limitation means that although ChatGPT can generate personalized feedback based on the classification model's predictions, there isn't an automatic mechanism in place to share this feedback directly with the students. This is a significant aspect of the study design, reflecting the exploratory and developmental nature of the project, where the focus is more on testing the feasibility of the AI-driven approach, rather than on real-time student interaction within an LMS environment.

3.2 Data Understanding

Collecting and comprehending xAPI data from e-learning activities.

3.2.1 Data Collection

The lesson will be shared with university student through email. Additionally, the general public will also contribute to this study and the lesson was be shared with the general public through communication channels.

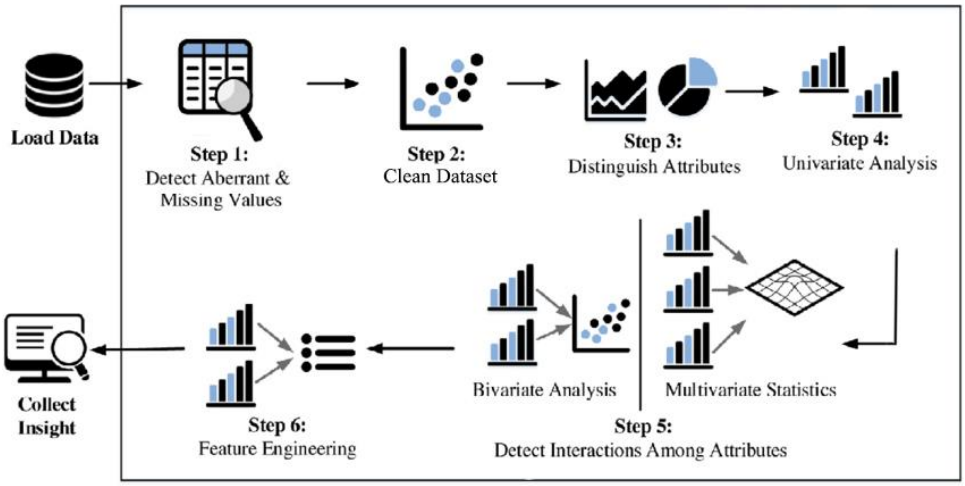
3.2.2 Data Exploration

With the collected xAPI data in hand, our next step is data exploration. This phase involves an in-depth examination of the dataset, with the objective of uncovering valuable insights. Through exploratory data analysis (EDA), we will unveil hidden patterns, identify data distributions, and pinpoint potential outliers.

These insights will play a pivotal role in guiding the subsequent data preparation and modeling phases. The steps of the EDA are summarized in Figure 17.

Figure 17

The Fundamental Steps of the Exploratory Data Analysis Process



Identifying irregular or erroneous data points, which could result from data entry errors or anomalies was done by the e-learning lesson and the LRS. Once the data has loaded from the LRS. Reformatting the data and examining and processing the data types (e.g., numerical, categorical) and the role of each attribute in the analysis. Detect missing values and decide how to handle them (e.g., imputation, removal). Also decide if outliers should be retained, transformed, or removed based on their impact on analysis and modeling.

In univariate analysis each individual attribute is analyzed in isolation. Common techniques include:

- **Summary Statistics:** Calculate basic statistics like mean, median, mode, standard deviation, and percentiles to understand the central tendency and variability of numerical attributes.
- **Histograms and Density Plots:** Visualize the distribution of numerical variables using histograms or kernel density plots.

To detect relationships between attributes we explore relationships between pairs of variables (bivariate analysis) and examine interactions among multiple variables (multivariate analysis).

Techniques include:

- **Scatterplots:** Visualize the relationship between two numerical variables.
- **Correlation Analysis:** Calculate correlation coefficients (e.g., Pearson, Spearman) to quantify the strength and direction of linear relationships.

- **Principal Component Analysis (PCA) and Factor Analysis**: Reduce dimensionality and explore patterns among multiple variables.

In feature Engineering we can create new features or variables based on existing ones to enhance the dataset's predictive power. Feature engineering can include:

- **Creating Interaction Terms:** Combining two or more variables.
- **Binning or Discretization:** Grouping continuous variables into discrete categories.
- **Feature Scaling**: Standardizing or normalizing numerical attributes.
- **One-Hot Encoding:** Converting categorical variables into binary indicators.
- **Feature Selection:** Identifying and retaining the most informative attributes for modeling.

3.3 Data Preparation

With the raw data at our disposal, the data preparation phase will come into play. Here, we will carefully pre-process the xAPI data and assessment results to ensure that they are in a suitable format for analysis. Data cleaning procedures will address any missing or inconsistent data points, while feature engineering may be employed to craft additional meaningful variables.

Since the study experiments with different algorithms, data needs to be transformed to different formats to suit each model. for example, the KNN primarily works with numerical and categorical data, so it's essential to transform to utilize techniques such as One-hot encoding to transform data.

Data will also need to be prepared to create a suitable prompt for ChatGPT. The prompt will include information about the lesson context and the predictions of the learning objectives pass of fail status.

3.4 Modeling

3.4.1 Model Selection

The core of our research lies in predictive modeling. Several algorithms will be tested:

- K-Nearest Neighbors (KNN)
- Decision Trees
- Random Forest
- Support Vector Machines (SVM)
- Logistic Regression
- Neural Networks (Deep Learning)

3.5 Evaluation

Selected models will undergo rigorous training and evaluation processes. A subset of the dataset will be used for model training, while cross-validation techniques will ensure robust evaluation. For performance metric, we will evaluate the accuracy, this will serve as benchmarks to assess the models' predictive prowess.

3.6 Deployment

The framework is ready to be applied at a larger scale. Using LMS and an entire curriculum made with xAPI technology.

Chapter 4: Results and Analysis

This chapter breaks down the acquired dataset and the results of the data analytics and AI application.

4.1 LRS Dashboard Insights

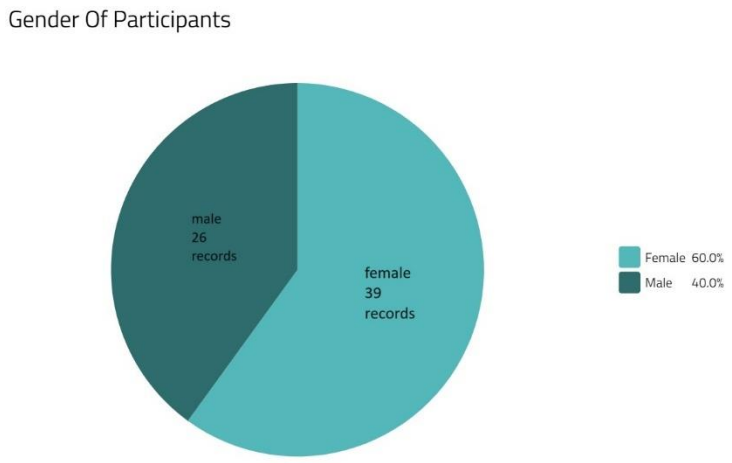
Looking at the dashboard we begin to have an understanding of the data acquired from the participants. 70 participants contributed to the dataset, 36 of those 70 people have reached the exit page. However, this doesn't necessarily mean that the rest did not complete the lesson, if the participant completes all the learning material and assessments, we consider their data complete.

Figure 18

The Total Number of Participants and Statements Over the Period of Two Weeks

Figure 19

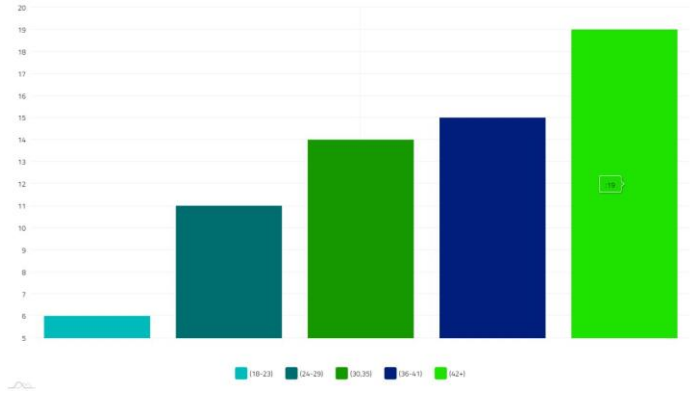
Gender of Participants



The gender distribution is 39 females and 26 males. The participants are spread across various age groups: 6 participants are aged 18-23, 11 in the 24-29 range, 14 are between 30-35 years, 15 fall in the 36-41 bracket, and the largest group of 19 participants are aged 42 and above. This diverse demographic profile provides a broad perspective on the learning experiences and outcomes of different age groups and genders in the study.

Figure 20

Age Groups



The average scores obtained by participants vary across different Bloom's levels. For Bloom's level 1 (Remembering), scores rose from an average of 8.2 to approximately 9.44. In Bloom's level 2 (Understanding), there was a marked increase from about 6.91 to 8.02. The most significant improvement is observed in Bloom's level 3 (Applying), where scores jumped from around 4.67 to 6.07. These results indicate substantial enhancements in learners' abilities across the different cognitive skills defined by Bloom's taxonomy.

Overall, the average score for all pre-assessments was about 6.59, indicating the baseline level of learners' knowledge and skills. After the educational interventions, the average score for all post-assessments increased to approximately 7.85. This rise in scores reflects the positive impact of the learning activities and materials on the learners' understanding and application of the content, spanning across various cognitive levels.

4.2 Exploratory Data Analysis (EDA)

To conduct an Exploratory Data Analysis (EDA) on this dataset, we'll go through several steps to understand the data better. EDA typically includes checking for missing values, understanding the distribution of variables, investigating relationships between features, and other statistical analyses.

4.2.1 Data Collection and Cleaning

There is a total of 3,452 xAPI statements for 70 actors exported from the LRS is JSON format. the following steps were taken:

1. Conversion to CSV: This step makes the data easier to overview, allowing you to identify patterns or inconsistencies more clearly compared to JSON format.
2. Column Selection: You streamline the dataset by keeping only vital columns. This focuses analysis on the most relevant data aspects like actor, verb, object, results, and Bloom's level.
3. Removing Special Characters: Cleaning up the 'actor.mbox' column ensures that the data is standardized and free of extraneous characters, which is crucial for accurate identification of actors.
4. Filling Blank Bloom Levels: By inputting missing values in the 'blooms-level' column, you maintain data integrity, ensuring that each record is complete and usable for analysis.
5. Deleting Irrelevant Interactions: Removing entries related to non-essential interactions like 'initial slide' or 'Certificate' ensures the dataset reflects meaningful learner engagement.
6. Handling Missing 'Duration' Values: Eliminating records with missing or NaN 'result.duration' values helps maintain the quality and reliability of the dataset.
7. Excluding 'Experienced' Verb Entries: Since 'left' verb entries provide the needed information, removing 'experienced' verbs avoids duplicating or irrelevant data.
8. Filling Blank Values: Ensuring there are no blanks in the dataset prevents issues during analysis where missing data could skew results.
9. Renaming Columns: This step improves data readability and simplicity, making subsequent data handling and analysis more efficient.

10. Ensuring Unique Actor Values: ensure that each 'actor' has a unique identifier. This is crucial for tracking individual learner progress and avoiding redundancy. Any duplicates in the dataset are identified and resolved, ensuring each entry represents a distinct user.
11. Removing Incomplete Attempts: This involves filtering out records where participants didn't complete the learning activity. To ensure that the data analysis reflects fully engaged learning experiences, thereby enhancing the reliability and relevance of the insights derived from the dataset.

After the initial cleaning 1268 xAPI statements left and 51 actors who fully completed the e-learning lesson remained.

Now the next step is to aggregate and transpose to prepare the data for the subsequent steps. Each row represents a unique actor, all values have been normalized, the columns are listed in Table 11 below:

Table 11

Dataset Transformed to be Analyzed

Columns	Description
Age	integer numbers (18-65)
Gender	Categorical (M, F)
LO1 duration, LO2 duration, LO3 duration	float (represents time in seconds)
LO1 pre-assessment, LO2pre-assessment, LO3 pre-assessment	float (score out of 100)

LO1 post-assessment, LO2post-assessment, LO3 post-assessment	float (score out of 100)

4.2.2 Summary Statistics

As mentioned earlier, in total 51 participants completed the course. The dataset includes both categorical (e.g., gender) and numerical variables (e.g., age, pre1, Lo1 duration). It covers pre and post-test scores, durations for learning objects, and overall study durations.

The summary statistics of this study show a broad range in participant ages, scores, and learning object durations. Participant ages vary from 18 to 56 years, with an average of around 35 years. This reflects a diverse age group. The scores, both pre and post assessments, exhibit a wide range, indicating varied levels of understanding and skill among participants, with some scoring as low as 0 and others achieving a full score of 100. In terms of learning objects, durations also display significant variability. For instance, the time spent on Learning Objective 3 (Lo3) ranges from about 61 to 5989 seconds, suggesting different levels of engagement or learning speeds among learners.

Figure 21

Summary Statistics

```
(            age        pre1        pre2        pre3       post1       post2  \
 count  51.000000   51.000000   51.000000   51.000000   51.000000   51.000000
 mean   35.098039   80.392157   47.345098   63.579552   92.156863   56.308123
 std     9.708254   40.097919   33.369101   26.380617   23.178760   35.149942
 min    18.000000    0.000000    0.000000   14.285714    0.000000    0.000000
 25%    29.000000  100.000000   28.600000   42.885714  100.000000   28.592857
 50%    33.000000  100.000000   42.900000   71.385714  100.000000   42.900000
 75%    42.000000  100.000000   71.400000   85.700000  100.000000  100.000000
 max    56.000000  100.000000  100.000000  100.000000  100.000000  100.000000

             post3  Lo1 duration  Lo2 duration  Lo3 duration  total_duartion  \
 count   51.000000     51.000000     51.000000     51.000000       51.000000
 mean    72.270028    141.396549    216.605510   1189.866824     1547.868882
 std     26.084729    132.019358    243.076908   1233.228949     1495.572374
 min     28.571429     11.934000     14.676000     61.232000      103.836000
 25%     57.100000     60.080500     87.761000    435.712000      580.341500
 50%     71.471429    110.408000    136.217000    757.163000      971.714000
 75%    100.000000    167.122000    240.065000   1392.783000     2001.184000
 max    100.000000    671.887000   1494.247000   5989.324000     7610.444000

        pre_percent  post_percent
 count    51.000000     51.000000
 mean     63.772269     73.578338
 std      25.033117     21.245228
 min       4.761905     23.823810
...
 Lo3 duration      0
 total_duartion    0
 pre_percent       0
 post_percent      0
 dtype: int64)
```

4.2.3 Univariate Analysis

To perform univariate analysis on xAPI data from, the first step is loading the data and then analyze the distribution of each variable. This will include generating appropriate visualizations such as histograms, bar charts, or box plots, depending on the nature of the data (numerical or categorical).

The dataset contains various variables related to the learning activity. Here's a quick overview of the columns:

- gender: Gender of the participant.
- age: Age of the participant.

- pre1, pre2, pre3: Pre-activity scores.
- post1, post2, post3: Post-activity scores.
- Lo1 duration, Lo2 duration, Lo3 duration: Duration of different learning objects.
- total_duration: Total duration of the activity.
- pre_percent: Percentage score before the activity.
- post_percent: Percentage score after the activity.

The univariate analysis on each of these variables will be focusing on their distribution. Starting by gender where the distribution between different genders is relatively balanced, with a slightly higher number of females. The age distribution is somewhat evenly spread, but it leans towards the younger demographic. This indicates a variation in age groups among the participants.

Figure 22

The Gender Distribution

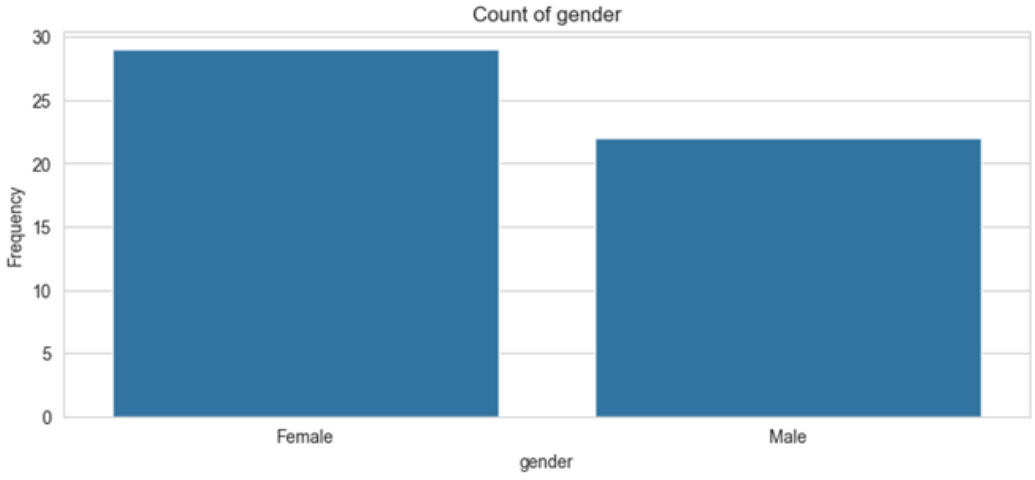
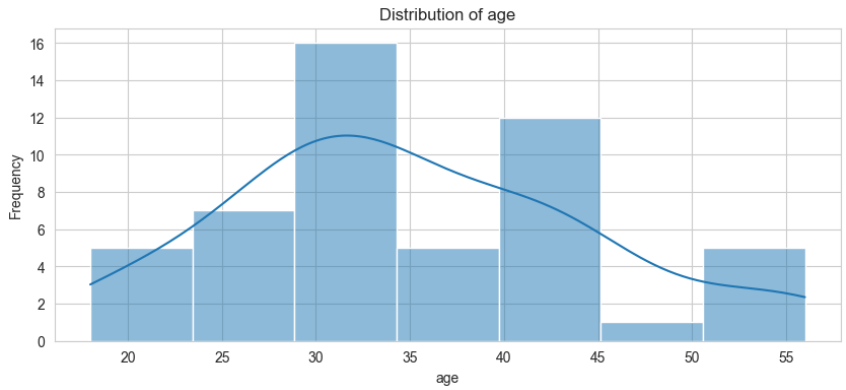


Figure 23

The Age Distribution



For Learning objective duration (Lo1 duration, Lo2 duration, Lo3 duration) corresponding each to a blooms level, they display varied distributions, with most learners spending a moderate amount of time on each learning object. There are some outliers, especially in Lo1 duration and Lo3 duration, indicating that a few learners spent significantly more time on these.

Figure 24

Box Plot of the Total Time Spent

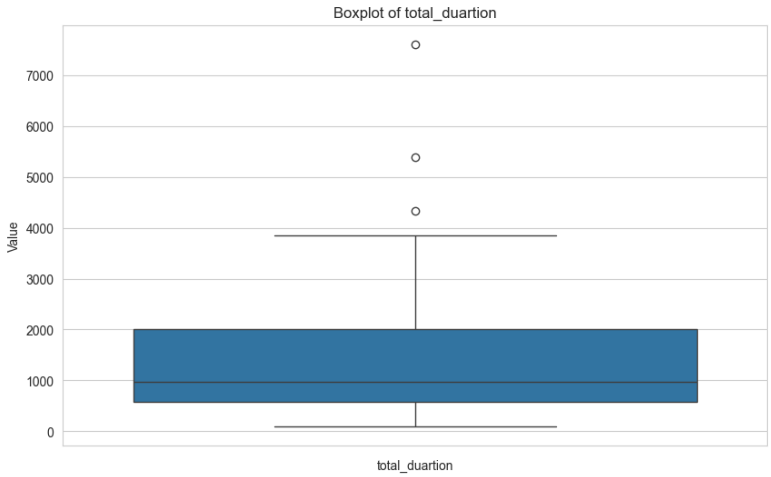


Figure 25

Box Plot of the Time Spent on LO1 (Blooms level1)

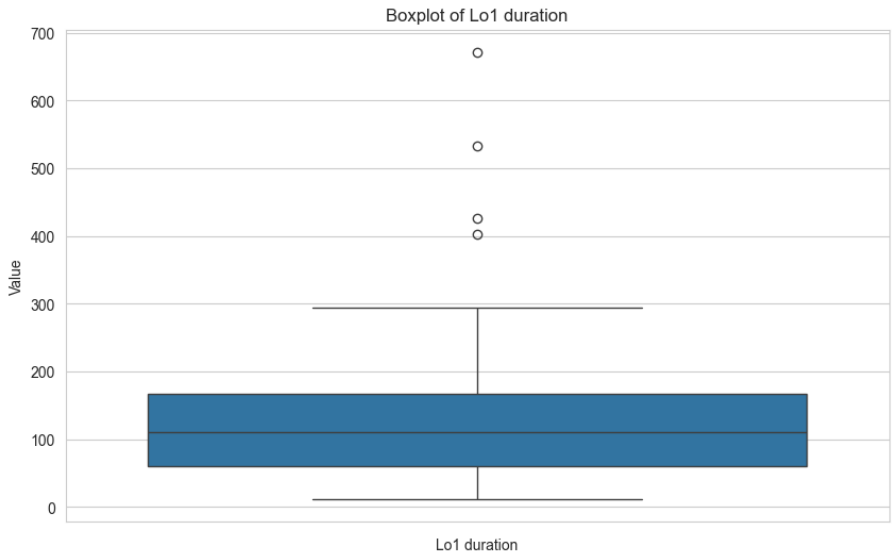


Figure 26

Time Spent on LO2 (Blooms level2)

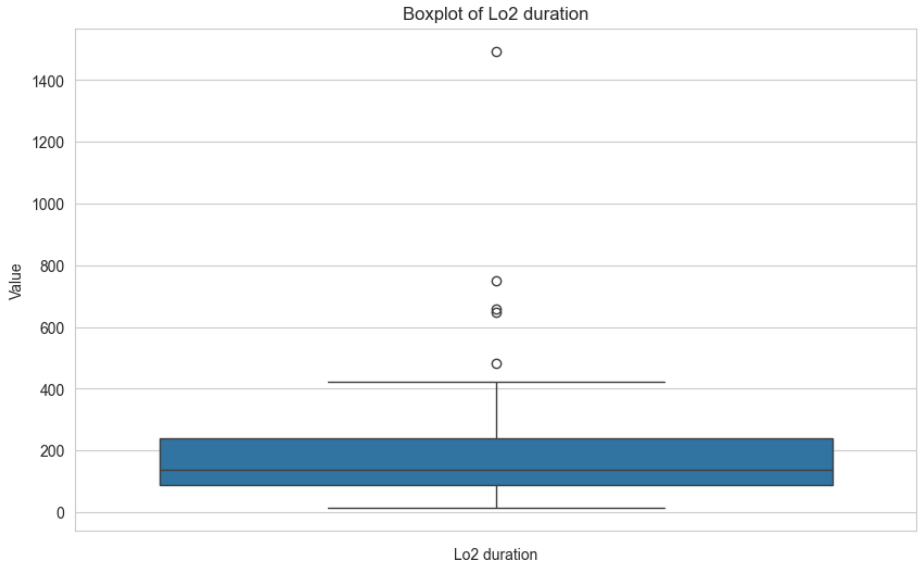
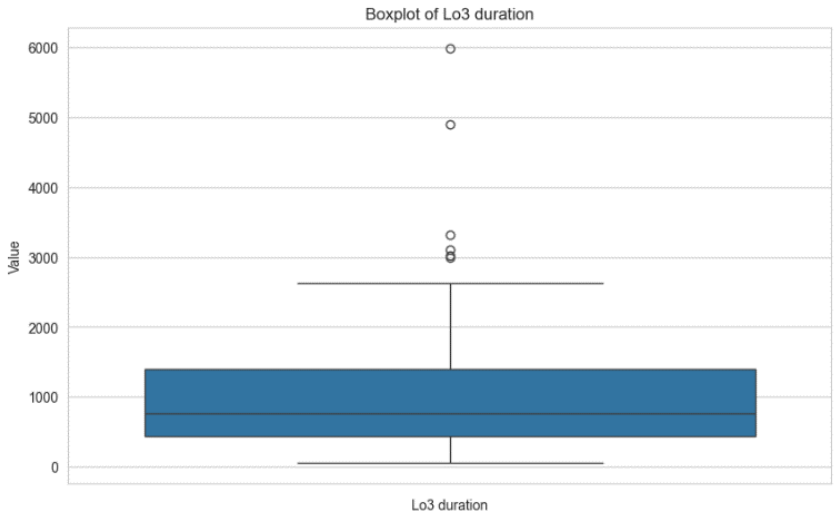


Figure 27

Time Spent on LO3 (Blooms level3)



The distributions of the scores vary. Some, like pre1 and post1, show a high frequency of perfect scores (100), which might indicate a relatively easy assessment at bloom level 1. Other scores like pre2, pre3, post2, and post3 are more spread out, suggesting a range of performances. It's notable that post2 and post3 show a significant number of participants scoring at the highest level. Overall, this indicates an improvement in score amongst participants. A calculated variables for the total scores were also analyzed. For pre_percent, post_percent (Total Percentage scores), These percentages give a sense of overall performance before and after the activity. The post-activity percentages (post_percent) seem to skew higher, suggesting an overall improvement.

Figure 28

Pre Assessment1 Score Distribution

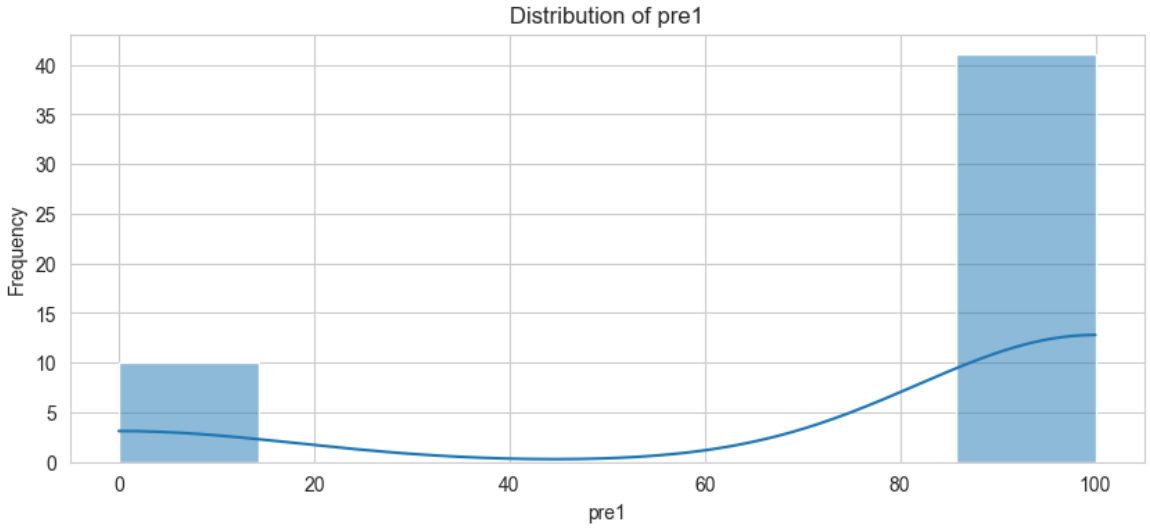


Figure 29

Pre Assessment2 Score Distribution

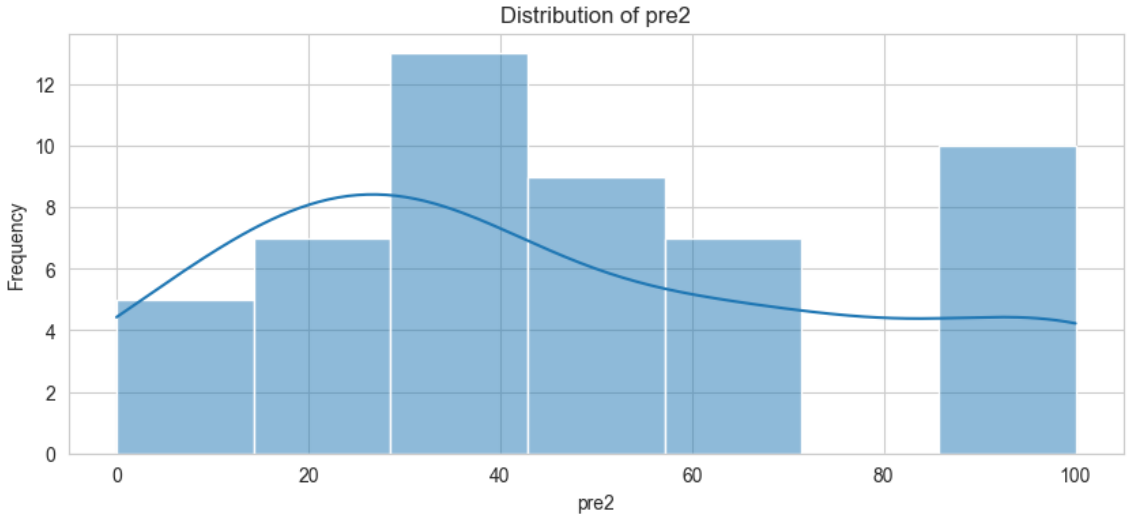


Figure 30

Pre Assessment3 Score Distribution

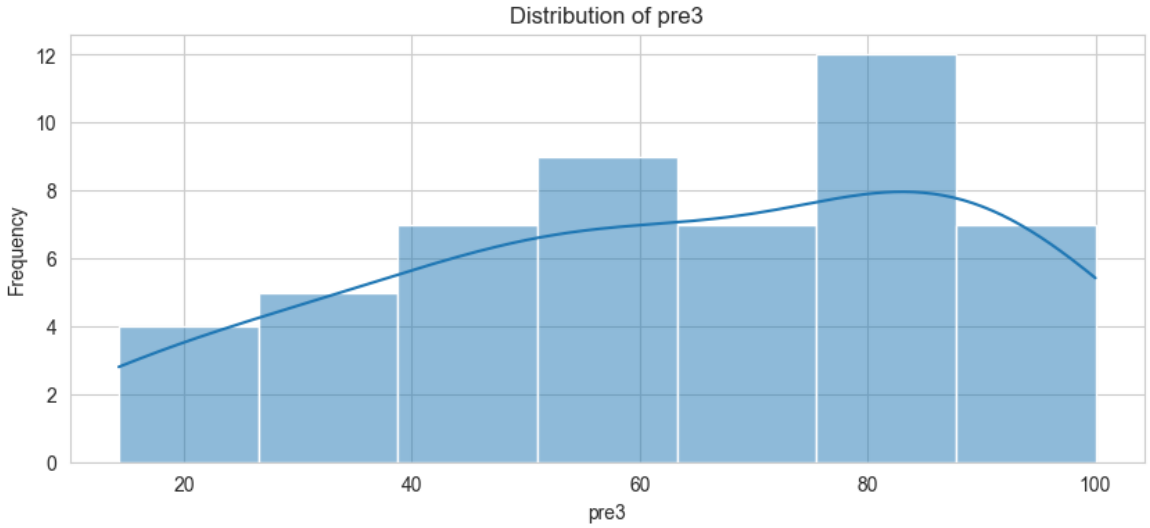


Figure 31

Pre Assessment Score Distribution

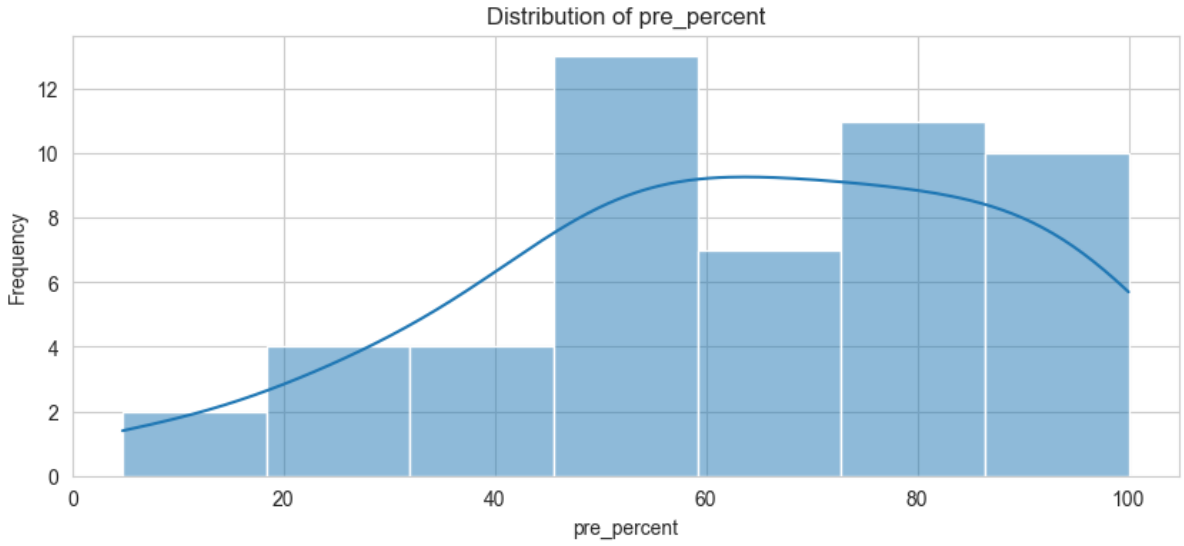


Figure 32

Post Assessment1 Score Distribution

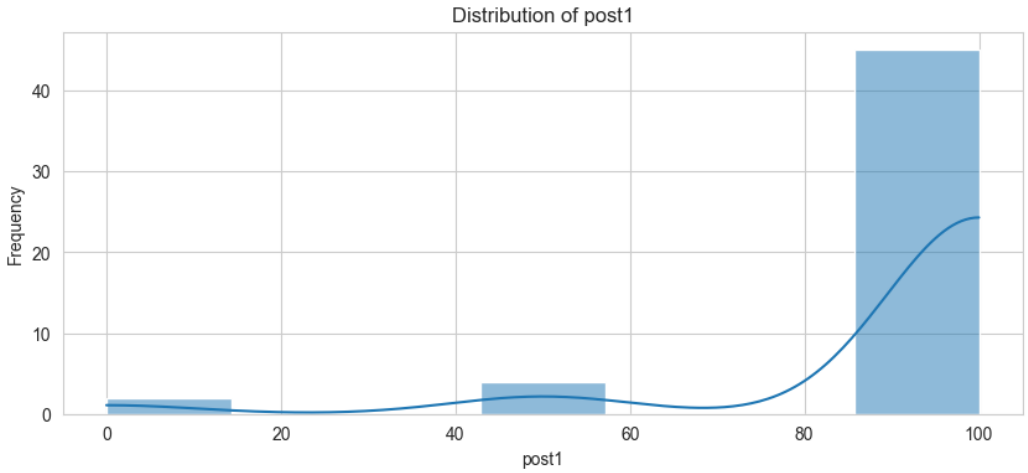


Figure 33

Post Assessment2 Score Distribution

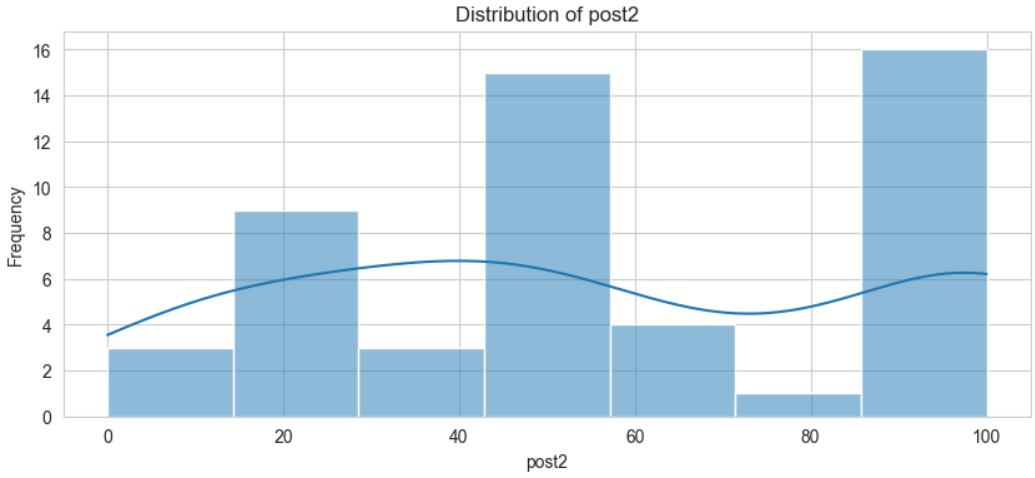


Figure 34

Post Assessment3 Score Distribution

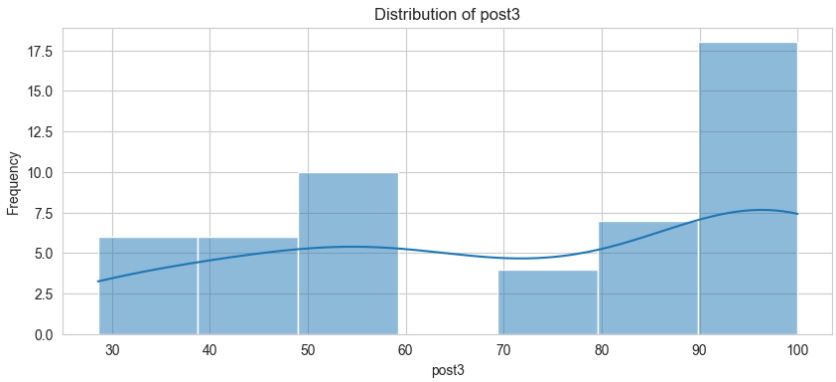
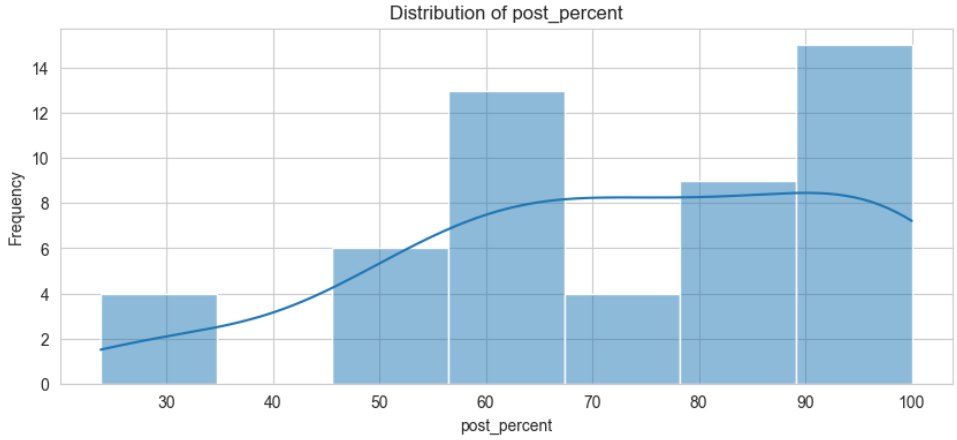


Figure 35

Post Assessment Score Distribution



Overall, the univariate analysis of xAPI data provides valuable insights into the characteristics of the participants and their engagement and performance in the learning activity. The score distributions suggest variations in learning outcomes, while the duration-related variables indicate differing levels of engagement. The age distribution offers a sense of

the demographic diversity of the participants. This analysis can be the foundation for more in-depth exploration.

4.2.4 Bivariate Analysis

Since the data contains xAPI information from a learning activity and relates to Bloom's taxonomy levels with pre and post assessment scores, we'll focus on analyzing relationships between key variables such as LO (Learning Objectives), Bloom's levels, pre and post assessment scores, grades, and pass/fail states. The Bivariate Analysis explores the relationships between the different variables, in this case, focusing on how pre and post assessment scores, grades, and pass/fail states are related to each other and to the Learning Objectives (LOs).

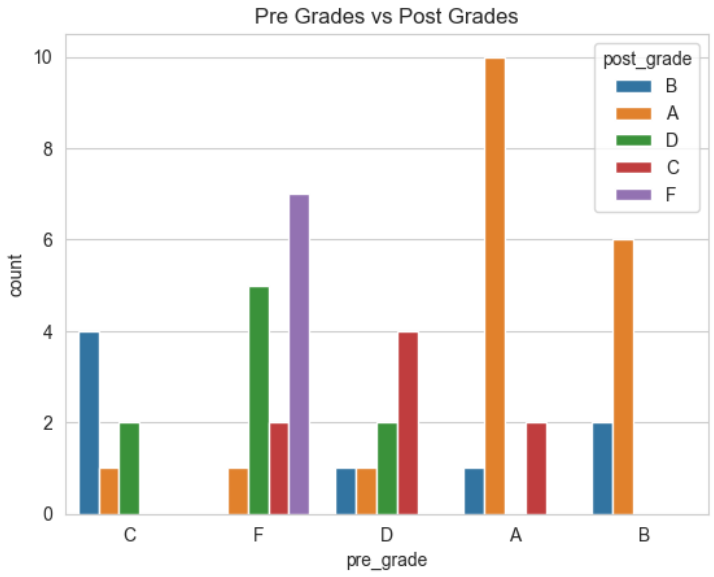
4.2.4.1 Pre vs Post Assessment

Figure 36

Pre vs Post Assessment Scores Scatter Plot

Figure 37

Pre Grades vs Post Grades Count Plot



The scatter plot in Figure 36 shows the relationship between pre and post assessment scores for different items (Pre1 vs Post1, Pre2 vs Post2, Pre3 vs Post3). A positive correlation can be observed, indicating that higher pre\-assessment scores generally correlate with higher post-assessment scores.

The count plot in Figure 37 displays the distribution of grades from pre to post assessments. It helps to observe the shift in grades from pre to post assessments, providing insight into whether there's a general improvement, decline, or stability in grades. In this case there seems to be an improvement in grades. For example, For Pre grades of A, B,C, none of participants fails the lesson, while the majority of students who failed the pre assessment have passed the final assessment.

Figure 38

Pre-Grade Binary vs Post Grade Binary Heatmap

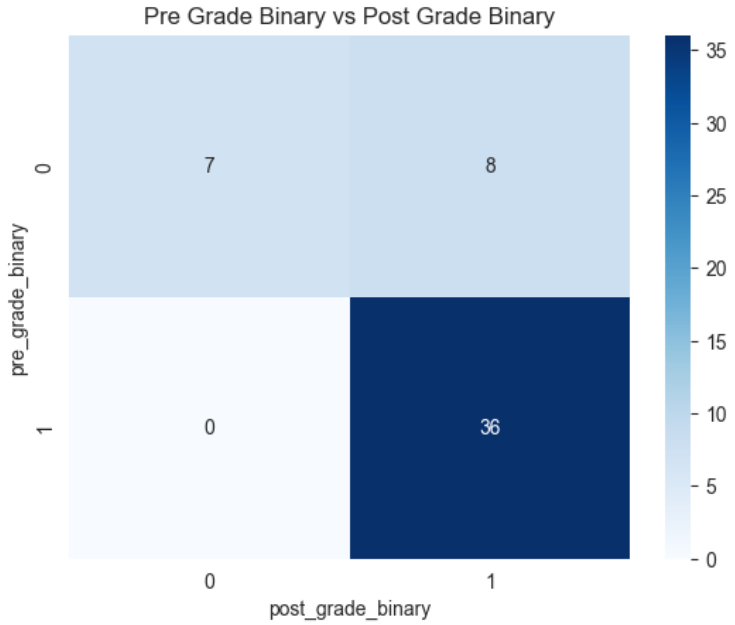
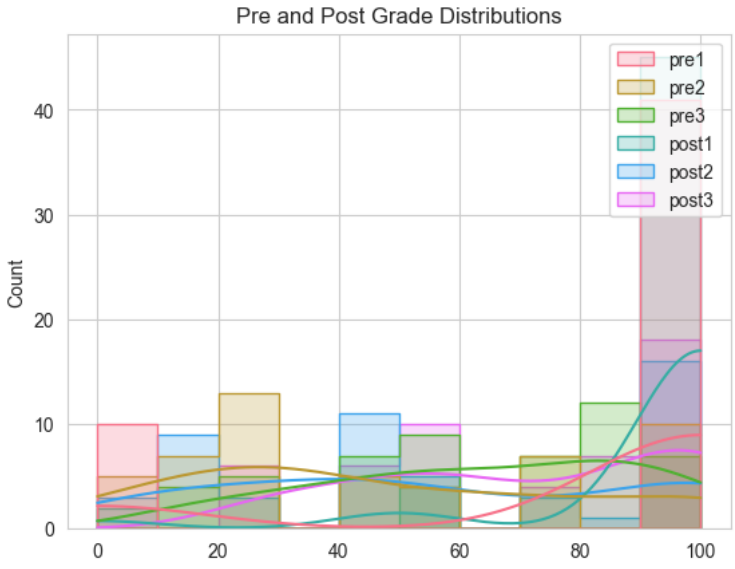


Figure 39

Pre and Post Grade Distributions Histogram



The heatmap in Figure 38 shows the relationship between binary representations of pre and post grades (pass/fail).

The distribution of changes from pass to fail or fail to pass from pre to post assessments can be seen. For example, a high count in a cell indicates many students moved from a particular pre\-grade state to a post-grade state. zero number of participants who passed the pre-assessment have failed the final assessment, in fact the majority of participants (36 people) passed both assessments, while 7 only have failed both.

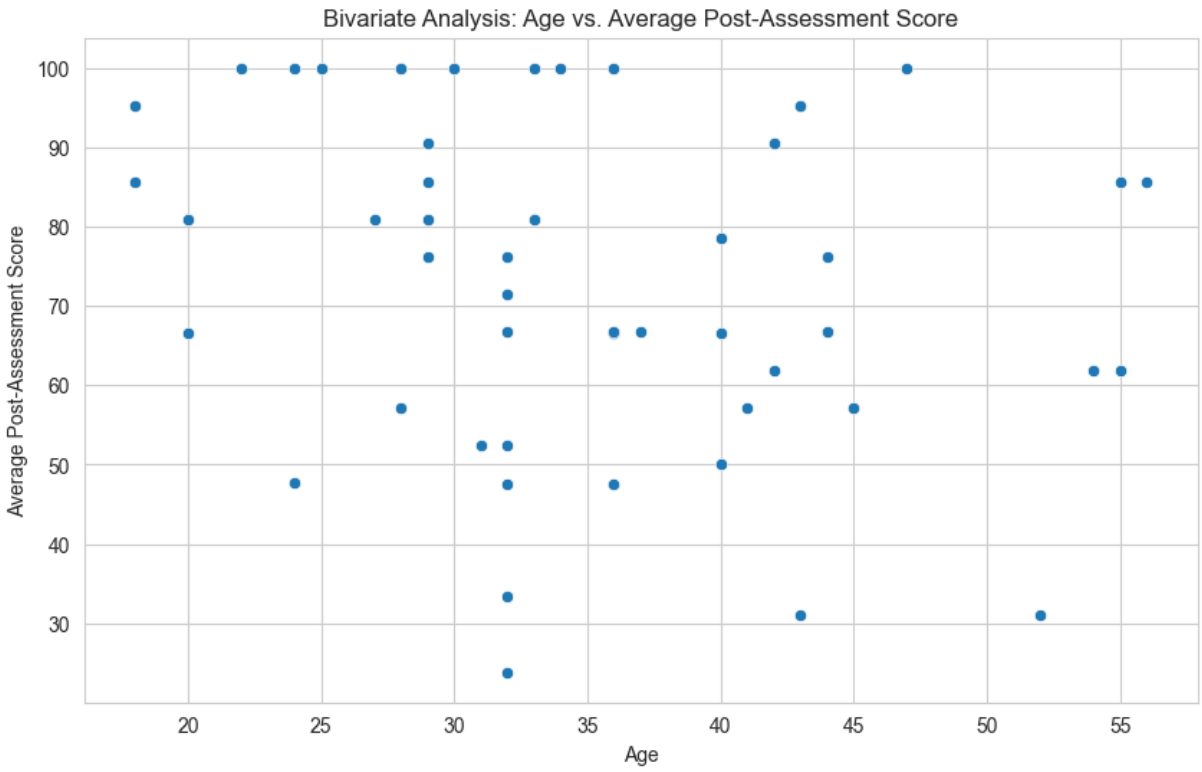
This histogram in Figure 39 displays the distribution of scores across pre and post assessments. It provides a visual representation of the spread and central tendency of scores, which is useful for understanding the overall performance of students in these assessments.

From these analyses, it is evident that there is a general correlation between pre and post assessment scores. The shift in grades from pre to post assessments could indicate the effectiveness of the learning activity or intervention. The binary grade analysis is particularly useful for understanding changes in pass/fail rates, which might reflect on the overall effectiveness of the teaching methodologies or learning materials used in the activity.

4.2.4.2 Age vs Post Assessment

Figure 40

Age vs. Average Post-Assessment Score



The scatter plot displays the relationship between age and the average post-assessment score. The data points are spread across various age groups and show a range of post-assessment scores. There doesn't appear to be a clear linear pattern indicating a strong relationship between age and the average post-assessment score. The scores vary significantly within each age group, suggesting that factors other than age might have a more pronounced influence on the post-assessment scores. There are no apparent outliers or extreme values that significantly deviate from the overall distribution. All age groups seem to be represented, but

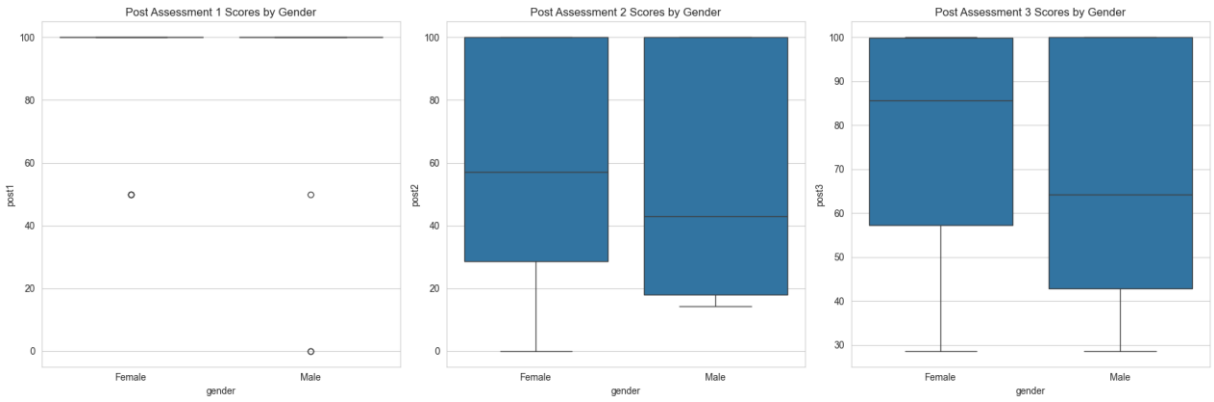
it's difficult to discern any trend or correlation between age and performance on the post-assessments.

In conclusion, based on this scatter plot, there isn't a clear or significant correlation between age and average post-assessment scores in this dataset. It's important to note that correlation does not imply causation, and other factors not considered in this analysis might influence the post-assessment scores. Further statistical analysis could provide more insights, especially when considering other variables in the dataset.

4.2.4.3 Gender vs Post Assessment

Figure 41

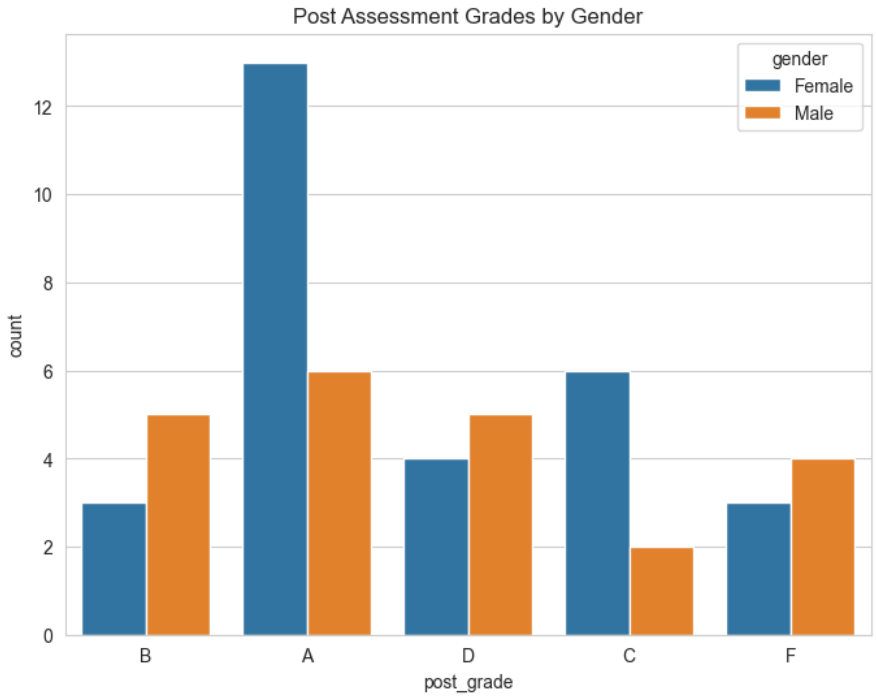
Box Plots of Post-Assessment Scores by Gender



The boxplots for post assessment scores (post1, post2, post3) show the distribution of scores for each gender. It appears that there are variations in the median and spread of the scores between genders across the different post assessments. Notably, in some assessments, females might have a slightly higher median score or a different interquartile range, indicating variation in performance.

Figure 42

Post Assessment Grades by Gender



The count plot for post assessment grades displays the distribution of grades (A, B, C, D, F) across genders. This visualization helps in understanding the grade distribution and how it varies between genders. Certain grades might be more prevalent in one gender compared to the other. for example, males are more likely to score an F even though there are less men than women in the dataset. Also, there are more than twice as many women scoring an A compared to men.

Figure 43

Post Assessment Pass/Fail State by Gender

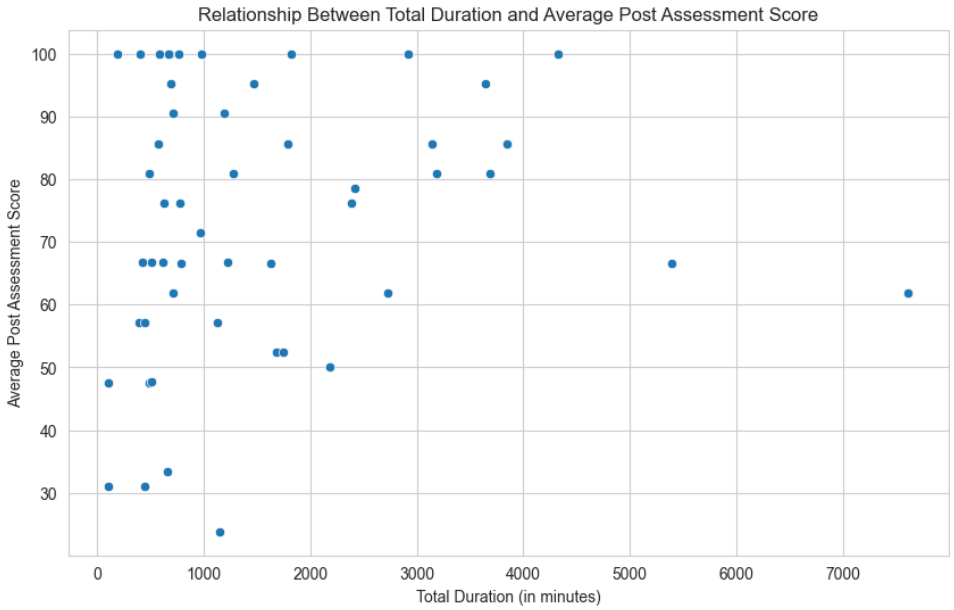
This count plot in Figure 43 illustrates the distribution of passing (1) and failing (0) states in post assessments for each gender. It provides a straightforward comparison of the proportion of students passing or failing between genders. It is clear than more men fail than women and more women pass the assessment than men.

In summary, while there are observable differences in post-assessment results between genders, it's important to consider these findings in the broader context of the learning environment.

4.2.4.4 Duration vs Post Assessment. The scatter plot in Figure 44 visualizes the relationship between the total duration of learning activities and the average post-assessment score. The data points are spread across a wide range of durations, suggesting variability in how much time learners spend on the activities. The post-assessment scores also vary, with a concentration of scores across different duration levels. There doesn't appear to be a strong linear correlation between total duration and average post-assessment score. While we might expect longer durations to correlate with higher scores (indicating more time spent learning leads to better performance), the data does not strongly support this assumption. There are a few outliers, particularly in the duration aspect. Some learners have exceptionally high total durations compared to others.

Figure 44

Relationship Between Total Duration and Average Post Assessment Score



This analysis suggests that while duration is an important factor in learning activities, it may not be a reliable predictor of assessment performance. It's also possible that some learners

achieve comprehension more quickly than others, resulting in shorter durations but similar or better assessment outcomes.

4.2.5 Multivariate Analysis

Figure 45

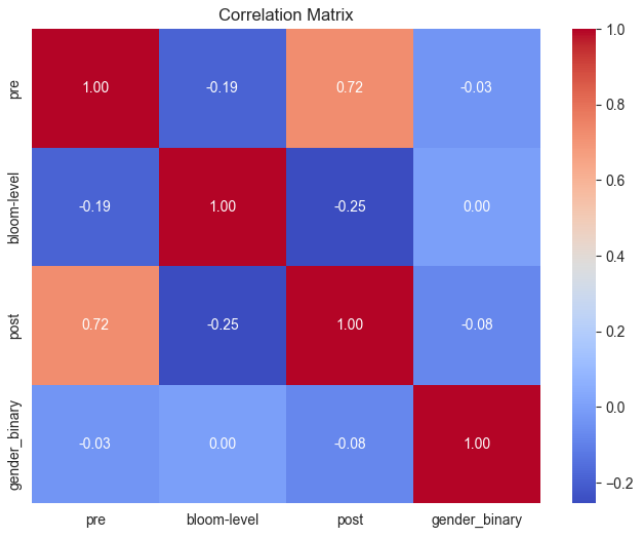
Summary of Expanded Dataset

```
(              pre  bloom-level        post
 count  153.000000   153.000000  153.000000
 mean    63.772269     2.000000   73.578338
 std     36.157136     0.819178   31.991069
 min      0.000000     1.000000    0.000000
 25%     28.600000     1.000000   42.900000
 50%     71.400000     2.000000   99.971429
 75%    100.000000     3.000000  100.000000
 max    100.000000     3.000000  100.000000,
 gender
 Female    87
 Male      66
 Name: count, dtype: int64)
```

The dataset was expanded, the columns consist of pre (pre assessments scores), post (post assessment scores), gender, blooms level.

Figure 46

Correlation Matrix



The correlation between pre (pre-assessment scores) and post (post-assessment scores) remains significant (0.72), indicating a strong relationship between these two variables. The bloom-level shows a relatively weaker negative correlation with both pre and post scores, consistent with our previous observations. The gender variable shows a very weak correlation with post scores. This suggests a slight negligible association between gender and post-assessment scores in this dataset.

4.2.6 Feature Engineering

Based on the assessment, the features that are going to be used are the pre-assessment scores and blooms-level to predict if a student will pass or fail the post assessment.

Creating the Target Variable, which will be a binary representation of pass/fail status, where 0 is for fail and 1 is for pass.

The features need to be transformed. Different models will be tested, there is a need to scale the pre scores to ensure they're on the same scale as other features. This is particularly important for algorithms that are sensitive to the scale of input data (like SVMs, k-NN, neural networks). The scores will be normalized to values 0-3, where zero is for fail, and 1 is for low achievers and 3 for high achievers.

4.3 Classification Models

Building and testing various machine learning models to predict whether students pass or fail based on their pre-grade and Bloom-level. The models chosen are K-Nearest Neighbors (KNN), Decision Trees, Random Forest, Support Vector Machines (SVM), Logistic Regression, and Neural Networks (Deep Learning).

The dataset contains several columns, but for our analysis, we'll focus on 'pre_grade', 'bloom-level', and 'post_grade_pass/fail'. The 'post_grade_pass/fail' column is our target variable, indicating whether a student passed or failed. 'pre_grade' and 'bloom-level' will be our features.

The data was split 80% for training and 20% for testing. We have 122 samples for training and 31 for testing.

The K-Nearest Neighbors (KNN) model achieved an accuracy of approximately 64.5% on the test data. The Decision Tree model achieved an accuracy of approximately 74.2%. Similar performance was observed by The Random Forest model and The Support Vector Machine. The Random Forest model achieving an accuracy of approximately 74.2% on the test data. While The Support Vector Machines (SVM) model achieved an accuracy of approximately 74.2% on the test data. The Logistic Regression model achieved a notably higher accuracy of approximately 93.5% on the test data.

For Neural Networks model. Given the relatively small size of the dataset, a simple neural network architecture was used. Achieving an accuracy of 80.6%.

To summarize, here are the accuracy scores for each model on the test data:

1. K-Nearest Neighbors (KNN): 64.5%
2. Decision Trees: 74.2%
3. Random Forest: 74.2%
4. Support Vector Machines (SVM): 74.2%
5. Logistic Regression: 93.5%
6. Neural Networks: 80.6%

Including a validation step, K-Fold Cross-Validation method was selected given we have a small dataset. The dataset is divided into 'k' subsets. Each time, one subset is used as the test set, and the rest are combined to form the training set. This process is repeated 'k' times, with each subset used exactly once as the test set. The final performance measure is the average of the performance on each fold. In this scenario, a 5-fold cross-validation for each model was used to evaluate performance more robustly.

To summarize, here are the accuracy scores for each model using 5-fold cross-validation:

1. K-Nearest Neighbors (KNN): 81.0%
2. Decision Trees: 81.6%
3. Random Forest: 81.6%
4. Support Vector Machines (SVM): 85.5%
5. Logistic Regression: 82.9%
6. Neural Networks: 85.5%

In Summary, Logistic Regression performed the best with the highest accuracy of 93.5% against the test set. But upon validation, The Support Vector Machines (SVM) and Neural Networks models show the highest average accuracy of 85.5%. The results indicate that more data is needed to improve predictions.

4.4 AI Feedback

The OpenAI's ChatGPT API was selected for this task, to setup the system we must specify the context shown in the screenshot in Figure 47.

Figure 47

Context fed to ChatGPT's API

```
You are a helpful kind teacher , you will provide
feedback and recommend actions  to the students
based on blooms taxonomy, depending on which
learning objectives they struggle with
```

Then at the prompting stage other information need to be fed this. This included the learning objectives, the corresponding blooms level of each learning objective, the predictions of the classification model. Figure 48 shows an example of a feedback given to a student who is predicted to pass LO1 (Define a Research paper) and LO2 (List the key components of a research paper) and fail LO3 (Describe each section of a research paper), which corresponds to blooms level 3 (Applying).

Figure 48

Example of a Customized Feedback

BUID

Feedback: You have demonstrated a good understanding of the definition of a research paper and have effectively listed the key components of a research paper. It is evident that you have a solid foundation in the basics of research paper writing.
To further improve your skills and ensure success in describing each section of a research paper, I recommend the following actions:

1. Take time to thoroughly review the structure and purpose of each section of a research paper (such as introduction, methodology, results, discussion, conclusion).
2. Practice analyzing and summarizing the key points or information that should be included in each section.
3. Work on developing your ability to connect the sections cohesively, ensuring a smooth flow of ideas throughout the paper.
4. Seek feedback from peers or instructors on your descriptions of each section and make necessary revisions for clarity and depth.

By focusing on these specific areas for improvement and continued practice, you will be able to enhance your skills in describing each section of a research paper effectively. Keep up the good work and continue seeking opportunities for growth in your research paper writing abilities.

Chapter 5: Discussion

This chapter summarizes the key finding and answers the research questions:

1. How can xAPI be integrated with AI technologies?
2. What xAPI attributes contributes to performance prediction?
3. How can learning prediction be utilized in adaptive learning?

5.1 RQ1: How can xAPI be Integrated with AI Technologies?

Integrating xAPI (Experience API) with AI (Artificial Intelligence) technologies can create powerful learning ecosystems that offer personalized, efficient, and deeply analytical educational experiences.

For data collection and analysis, xAPI tracks and records learning experiences in just about any type of learning materials in a consistent format, storing them in a Learning Record Store (LRS). This data can include anything from course completion to interactive elements within learning modules. AI algorithms can analyze this vast and varied xAPI data to identify patterns, learning behaviors, and potential areas for improvement.

AI can use xAPI data to understand a learner's strengths, weaknesses, preferences, and pace. AI can predict future learning outcomes based on past performance data captured by xAPI. For instance, it might identify students at risk of falling behind.AI can automate the generation of personalized feedback on assignments or assessments, based on the data collected by xAPI.

This study suggested a framework for applying xAPI-AI integration shown in Figure 12. It was shown through investigation that it was a feasible application. xAPI data in this context

was sending information about students' scores per learning outcomes based on blooms level. The data was used to predict student performance with a relatively high accuracy using classification algorithms, the predictions then were fed into an AI to provide personalized feedback. However, this study was applied on a single lesson with three learning outcomes corresponding to three blooms levels with limited participation. The results of the EDA process might vary depending on the context of application; however, the recommended pipeline can be adapted in institutions that already use xAPI and xAPI-supported Learning Management Systems with complex dashboards that can benefit from the integration of ML plugins to enable this framework to happen and advance adaptive learning with better utilized xAPI insights.

In summary, the integration of xAPI with AI technologies can significantly enhance the learning experience by making it more personalized, adaptive, and insightful. It leverages the strengths of both - xAPI's comprehensive data capturing capabilities and AI's powerful data analysis and predictive modeling.

5.2 RQ2: What xAPI Attributes Contributes to Performance Prediction?

In this study's context several attributes were examined: Age, Gender, Duration at each learning objective, Bloom's level for each learning objective, Pre and Post tests per learning objective. However, xAPI can produce just about any type of data from the learning experience.

It was shown that the duration may not a reliable predictor of student performance. Students achieve similar scores at a variant comprehension speed. Still duration is considered an important factor in learning activities, it is worth experimenting with duration as a

categorical relative attribute to the learning activity, for example (skipped, moderate time, excessive time).

Similarly, the age attribute showed a great variation at all age groups. Age was not a key attribute in this learning context. However, this might differ when dealing with different subject matter such Media Literacy or History for example.

There is a slight difference in between genders. Females achieved somewhat better, keeping in mind that female participants count is higher than males, so when it comes to correlation and statistical analysis, the gender attribute has shown a weak correlation to student performance.

Blooms level showed a moderate correlation to assessment performance, even in a limited context with only three learning objectives associated. A learner's competency history will likely provide deeper insights much beyond the bloom's level and more specific the bloom's verbs, for example students who have poor cognitive skills related to mathematics(solve) might struggle with physics (solve).

The attribute with the highest correlation was the pre-assessment scores. Pre-assessments take many forms such as quizzes, in-class activities, online activities...etc. Pre-assessments serve as a powerful indicator of student performance by identifying prior knowledge, setting benchmarks for growth, and allowing for customized learning experiences. These assessments even in traditional learning have always been a reliable indicator used by educators to tailor their teaching strategies to meet the varied needs of their students and predict their performance.

Other attributes we recommend looking into in future work are:

1. Engagement Data: measure student's level of interest and engagement with the content.
2. Completion Rates: Tracking which learning activities have been completed and which haven’t.
3. Interactions with Learning Materials: measure if the student has interacted with all learning activities.
4. Learning Pathways: By documenting the order in which the students access the material.
5. Social Learning Interactions: xAPI is capable of tracking interactions in social learning environments, such as discussion forums and group projects, providing insights into collaborative skills and engagement with peers.
6. Access count: The number of times the students access the learning content.

5.3 RQ3: How can Learning Prediction be Utilized in Adaptive Learning?

Predictive Analysis helps setting realistic and achievable learning goals for students, based on their progress and performance trends. It can also help in improving resource allocation by identifying which students need more support and what type of resources (e.g., tutoring, remedial classes, advanced materials) are most effective for different learner groups.

In this study the learning predictions were used to provide personalized feedback to the students. This feedback considers the blooms level to provide actionable recommendations.

In future work when predictive analytics forecasts which topics or skills a student might struggle with or excel in, the system adjust the learning path accordingly. This means students

can be directed towards content that challenges them appropriately, using course recommendations suggested by the personalized feedback.

Chapter 6: Conclusion

This study delves into the innovative intersection of Artificial Intelligence (AI) and the Experience API (xAPI) to pioneer a new paradigm in personalized learning experiences within the educational technology domain. With the advent of digital learning environments, there exists a vast potential to harness detailed data on student interactions for enhancing learning outcomes. The current work is motivated by the underutilized capabilities of xAPI in educational settings and the emerging potential of AI to transform these data into actionable insights, thereby facilitating a more individualized learning experience.

At the core of this paper is the proposal and development of an AI-driven framework that integrates with xAPI data to predict student performance and tailor learning experiences accordingly. The Experience API (xAPI) is a specification that enables the collection of data about a wide range of experiences a person has (online and offline). This data provides a comprehensive view of the learner's journey, capturing every digital footprint in the learning ecosystem. However, the sheer volume and complexity of this data necessitate the development of tools to distill actionable insights. Here, AI technologies, particularly machine learning models, come into play by analyzing these data streams to predict outcomes and recommend personalized feedback.

Adopting the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology to tackle this research problem. The process begins with a deep dive into the business understanding phase, where the educational context is thoroughly analyzed, revealing a gap in effectively utilizing learning analytics.

The data flow design is meticulously planned to capture and process xAPI statements, reflecting various learner interactions with the educational content. The study suggests attaching learning objectives and Bloom's taxonomy levels to xAPI data, enhancing the semantic richness of the dataset. This creates a more informed dataset then feeds into AI models designed to predict student performance across different learning objectives.

In this study, key attributes such as age, gender, time spent on each learning objective, Bloom's taxonomy level for each objective, and scores from pre and post-tests were analyzed to determine their correlation with student performance. It was found that while some attributes like duration spent on tasks and age varied significantly without a clear correlation to performance outcomes, pre-assessment scores stood out as a reliable predictor of student success. This indicates that understanding a student's prior knowledge and abilities can significantly enhance the personalization of learning experiences. Although gender showed a slight difference in performance, with females marginally outperforming males, this attribute demonstrated a weak correlation overall. Meanwhile, Bloom's taxonomy level indicated a moderate correlation, suggesting that deeper insights could be gained from analyzing a learner's competency history in relation to specific cognitive skills.

The study highlights the complexity of predicting student performance based on singular data points and emphasizes the potential of using a combination of attributes for a more nuanced understanding. For future work the paper recommends further exploration of attributes such as engagement data, completion rates, and social learning interactions to enrich the predictive model. These additional factors could provide a more holistic view of a student's learning journey, capturing their engagement level, progression through materials, and interaction within learning communities.

By leveraging classification algorithms, student pass/fail state were predicted per learning outcomes and yielding an accuracy of 93.5 %. This predictive capability allows for the proactive tailoring of learning paths and interventions even before traditional assessments could reveal such needs, which can be explored farther in future works.

Furthermore, the dissertation explores the use of ChatGPT, an advanced AI, to generate personalized feedback for students based on their predicted performance and areas of struggle. This feedback is crafted to be accessible and actionable, guiding students towards practices, or concepts they need to focus on. The use of AI here transcends mere prediction, venturing into the realm of personalized tutoring and support, thereby enhancing the learning experience significantly.

Research findings underscore the transformative potential of integrating AI with xAPI for personalized learning. The study demonstrates that AI algorithms can effectively interpret xAPI data, enabling real-time adjustments in the learning experience tailored to individual learner profiles. This not only can potentially enhance learner engagement but also significantly improve learning outcomes.

For educators and e-learning professionals, this study offers a blueprint for harnessing the power of AI and xAPI data to create more responsive and adaptive learning environments. To help gear towards a shift from a one-size-fits-all approach to education, moving towards a more personalized, learner-centered model. Furthermore, the research contributes to the academic discourse on AI in education, providing a practical framework for future studies and implementations.

In conclusion, the dissertation represents a step towards realizing the full potential of AI and xAPI in crafting personalized learning experiences. By intelligently analyzing detailed

data on learner interactions, the study illustrates how educational technologies can be leveraged to meet the unique needs of each student, thereby democratizing education and making learning more effective and engaging. The integration of AI with xAPI as explored in this dissertation not only enhances the educational landscape but also opens new avenues for research and innovation in the field of learning analytics and adaptive learning systems.

References

Alonso-Fernández, C., Calvo-Morata, A., Freire, M., Martínez-Ortiz, I., & Fernández-Manjón, B. (2023). Evidence-based evaluation of a serious game to increase bullying awareness. *Interactive Learning Environments*, *31*(2), 644–654. https://doi.org/10.1080/10494820.2020.1799031

Alonso-Fernández, C., Martínez-Ortiz, I., Caballero, R., Freire, M., & Fernández-Manjón, B. (2020). Predicting students' knowledge after playing a serious game based on learning analytics data: A case study. *Journal of Computer Assisted Learning* , 350–358.

Anderson, L., & Krathwohl, D. (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives: complete edition*. https://eduq.info/xmlui/handle/11515/18824?locale-attribute=en

Baker, R., & Siemens, G. (2014). Educational Data Mining and Learning Analytics. In *The Cambridge Handbook of the Learning Sciences* (pp. 253–272). Cambridge University Press. https://doi.org/10.1017/CBO9781139519526.016

Bakharia, A., Corrin, L., De Barba, P., Kennedy, G., Gašević, D., Mulder, R., Williams, D., Dawson, S., & Lockyer, L. (2016). A conceptual framework linking learning design with learning analytics. *ACM International Conference Proceeding Series, 25-29-April-2016*, 329–338. https://doi.org/10.1145/2883851.2883944

Calvo-Morata, A., Alonso-Fernández, C., Pérez-Colado, I., Freire, M., Martínez-Ortiz, I., & Fernández-Manjón, B. (2019). Improving Teacher Game Learning Analytics Dashboards through ad-hoc Development. *JUCS - Journal of Universal Computer Science 25(12): 1507-1530*, *25*(12), 1507–1530. https://doi.org/10.3217/JUCS-025-12-1507

Cano, A. R., Fernández-Manjón, B., & García-Tejedor, Á. J. (2018). Using game learning analytics for validating the design of a learning game for adults with intellectual disabilities. *British Journal of Educational Technology*, *49*(4), 659–672. https://doi.org/10.1111/BJET.12632

Chen, C. M., & Chang, C. (2019). A Chinese ancient book digital humanities research platform to support digital humanities research. *Electronic Library*, *37*(2), 314–336. https://doi.org/10.1108/EL-10-2018-0213/FULL/XML

Chen, C. M., & Wang, W. F. (2020). Mining Effective Learning Behaviors in a Web-Based Inquiry Science Environment. *Journal of Science Education and Technology 2020 29:4*, *29*(4), 519–535. https://doi.org/10.1007/S10956-020-09833-9

del Molino, J., Bibiloni, T., & Oliver, A. (2020). Keys for successful 360° hypervideo design: A user study based on an xAPI analytics dashboard. *Multimedia Tools and Applications*, *79*(31–32), 22771–22796. https://doi.org/10.1007/S11042-020-09059-2/TABLES/4

Durojaiye, A. B., Snyder, E., Cohen, M., Nagy, P., Hong, K., & Johnson, P. T. (2018). Radiology Resident Assessment and Feedback Dashboard. *Https://Doi.Org/10.1148/Rg.2018170117*, *38*(5), 1443–1453. https://doi.org/10.1148/RG.2018170117

Fernández-Morante, C., Cebreiro-López, B., Rodríguez-Malmierca, M. J., & Casal-Otero, L. (2021). Adaptive Learning Supported by Learning Analytics for Student Teachers' Personalized Training during in-School Practices. *Sustainability 2022, Vol. 14, Page 124*, *14*(1), 124. https://doi.org/10.3390/SU14010124

Heinemann, B., Ehlenz, M., Görzen, S., & Schroeder, U. (2022). xAPI Made Easy: A Learning Analytics Infrastructure for Interdisciplinary Projects. *International Journal of*

Online and Biomedical Engineering (IJOE), *18*(14), 99–113. https://doi.org/10.3991/IJOE.V18I14.35079

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education*, *57*(4), 542–570. https://doi.org/10.1111/EJED.12533

Liu, M., & Yu, D. (2023). Towards intelligent E-learning systems. *Education and Information Technologies*, *28*(7), 7845–7876. https://doi.org/10.1007/S10639-022-11479-6

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence Unleashed: An argument for AI in Education*. 60. https://www.researchgate.net/publication/299561597_Intelligence_Unleashed_An_argument_for_AI_in_Education

Manso-Vazquez, M., Caeiro-Rodriguez, M., & Llamas-Nistal, M. (2018). An xAPI Application Profile to Monitor Self-Regulated Learning Strategies. *IEEE Access*, *6*, 42467–42481. https://doi.org/10.1109/ACCESS.2018.2860519

Mohammad, A. S., Al-Kaltakchi, M. T. S., Alshehabi Al-Ani, J., & Chambers, J. A. (2023). Comprehensive Evaluations of Student Performance Estimation via Machine Learning. *Mathematics 2023, Vol. 11, Page 3153*, *11*(14), 3153. https://doi.org/10.3390/MATH11143153

Nouira, A., Cheniti-Belcadhi, L., & Braham, R. (2019). An ontology-based framework of assessment analytics for massive learning. *Computer Applications in Engineering Education*, *27*(6), 1343–1360. https://doi.org/10.1002/CAE.22155

Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence*, *2*, 100020. https://doi.org/10.1016/j.caeai.2021.100020

Patricia L. Smith, & Tillman J. Ragan. (2012). *Instructional Design, 3rd Edition*.

Plass, J. L., & Pawar, S. (2020). Toward a taxonomy of adaptivity for learning. *Journal of Research on Technology in Education*, *52*(3), 275–300. https://doi.org/10.1080/15391523.2020.1719943

Ruano, I., Estévez, E., Gámez, J., & Gómez, J. (2023). Standards for the Integration of Online Laboratories With Learning Management Systems. *IEEE Access*, *11*, 125267–125290. https://doi.org/10.1109/ACCESS.2023.3330666

Rustici Software. (n.d.). *xAPI.com Homepage: What is xAPI (the Experience API)*. Xapi.Com. Retrieved October 10, 2023, from https://xapi.com/

Samuelsen, J., Chen, W., & Wasson, B. (2021). Enriching context descriptions for enhanced LA scalability: a case study. *Research and Practice in Technology Enhanced Learning*, *16*(1), 1–26. https://doi.org/10.1186/S41039-021-00150-2/TABLES/4

Santamaría-Bonfil, G., Escobedo-Briones, G., Perez-Ramírez, M., & Arroyo-Figueroa, G. (2019). A Learning Ecosystem for Linemen Training based on Big Data Components and Learning Analytics. *JUCS - Journal of Universal Computer Science 25(5): 541-568*, *25*(5), 541–568. https://doi.org/10.3217/JUCS-025-05-0541

Schröer, C., Kruse, F., & Gómez, J. M. (2021). A Systematic Literature Review on Applying CRISP-DM Process Model. *Procedia Computer Science*, *181*, 526–534. https://doi.org/10.1016/J.PROCS.2021.01.199

Shum, L. C., Rosunally, Y., Scarle, S., & Munir, K. (2023). Personalised Learning through Context-Based Adaptation in the Serious Games with Gating Mechanism. *Education and Information Technologies*, *28*(10), 13077–13108. https://doi.org/10.1007/S10639-023-11695-8/TABLES/1

Siemens, G. (2013). Learning Analytics: The Emergence of a Discipline. *American Behavioral Scientist*, *57*(10), 1380–1400. https://doi.org/10.1177/0002764213498851

Vidal, J. C., Rabelo, T., Lama, M., & Amorim, R. (2018). Ontology-based approach for the validation and conformance testing of xAPI events. *Knowledge-Based Systems*, *155*, 22–34. https://doi.org/10.1016/J.KNOSYS.2018.04.035

Wu, Y., Guo, S., & Zhu, L. (2020). Design and implementation of data collection mechanism for 3D design course based on xAPI standard. *Interactive Learning Environments*, *28*(5), 602–619. https://doi.org/10.1080/10494820.2019.1696842

Yurtkan, K., Adalier, A., & Tekgu, U. (2023). Student Success Prediction Using Feedforward Neural Networks. *Romanian Journal of Information Science and Technology*, *26*(2), 121–136. https://doi.org/10.59277/ROMJIST.2023.2.01

Zhao, D., Playfoot, J., De Nicola, C., Guarino, G., Bratu, M., Di Salvadore, F., & Muntean, G. M. (2022). An Innovative Multi-Layer Gamification Framework for Improved STEM Learning Experience. *IEEE Access*, *10*, 3879–3889. https://doi.org/10.1109/ACCESS.2021.3139729

Appendices

Appendix A

Table 12

Selected Studies

code	Title	Year	AI and xAPI integration	xAPI specifications	Description
S1	A learning ecosystem for linemen training based on big data components and learning analytics (Santamaría-Bonfil et al., 2019)	2019	collects xAPI data from simulations and trainees self-report their emotional state, then uses clustering algorithms to select learning paths.	Plain xAPI profile +TinCan's registry extensions to capture emotions	Uses emotional state to select learning paths. Presents a framework to collect data from non-xAPI compliant means. capturing semantic meaning of description texts would be an improvement when selecting a learning path. Although the system has been useful.
S2	Student Success Prediction Using	2023	Prediction Using Feedforward Neural	Not used	91.95% (exact +one grade difference accuracy) behavioural data is more indicative

	Feedforward Neural Networks (Yurtkan et al., 2023)		Networks and xAPI data		of student performance than attribute data. Using behaviour and student profile attributes to gather only improved the predictions by 1.22%.
S3	Improving teacher game learning analytic dashboards through ad-hoc development (Calvo-Morata et al., 2019)	2019	No use of AI, data analytic dashboard only	xAPI-SG	creating analytical dashboards for serious games. learning dashboards made with xAPI data provided value to teachers
S4	An ontology-based framework of assessment analytic for massive	2019	no AI, ontology for assessment context	xAPI	ontology-based model for xAPI data. ontology can help classify semantically the real level of learners according to their

	learning (Nouira et al., 2019)				assessment performance
S5	Personalised Learning through Context-Based Adaptation in the Serious Games with Gating Mechanism (Shum et al., 2023)	2023	no AI,only game logic	xAPI-SG	game content is adapted to the player's performance by adjusting the difficulty of the learning content within the game using I-PLATO. The framework improves interoperability and content delivery to the game engine
S6	Mining Effective Learning Behaviours in a Web-Based Inquiry Science Environment	2020	no AI, lag sequential analysis	custom profile based on xAPI	sequential pattern mining can explore the difference between learners with high and low learning performance. learners with high learning performance exhibited

	(Chen & Wang, 2020)				continual operation behaviours followed by the sequence of the designed inquiry learning materials in their inquiry learning processes
S7	Keys for successful 360° hyper video design: A user study based on an xAPI analytics dashboard (del Molino et al., 2020)	2020	No, learning analytics	ADL video+TinCan registry	presented platform helps to analyse how users behave with omnidirectional interactive productions. xAPI is suited to handle low-level micro transactions even in small spans of time
S8	Ontology-based approach for the validation and conformance	2018	no, ontology of xAPI statements	ADL, ADB	The semantics of the proposed ontology is controlled by axioms and integrity constraints to ensure the correctness of

	testing of xAPI events (Vidal et al., 2018)				statements. Results show that the datasets comply with most part of the standard. However, the activities model is partially supported.
S9	Design and implementation of data collection mechanism for 3D design course based on xAPI standard (Wu et al., 2020)	2020	no, data collection only	custom profile based on xAPI	xAPI data analysis for 3d interactions. xAPI can track mouse and keyboard movements and students learning paths
S10	Evidence-based evaluation of a serious game to increase bullying	2023	yes, prediction models with different algorithms to predict awareness level comparing	xAPI-SG	establishing a process for evidence-based evaluations of the effectiveness of serious games. xAPI is an advantageous tool that simplifies collection,

	awareness (Alonso-Fernández et al., 2023)		interactions to post-game tests		processing and analysis of interaction data. Game design affects the quality of predictions.
S11	A Chinese ancient book digital humanities research platform to support digital humanities research (Chen & Chang, 2019)	2019	no, uses data to improve usability	ADL	using xAPI to understand user's perception. xAPI provides insights about the user experience that are beneficial to improve usability of a platform
S12	An xAPI Application Profile to Monitor Self-Regulated Learning Strategies (Manso-	2018	no	custom profile based on xAPI	standardization of SRL traces to enable data collection from multiple sources. xAPI is suitable to represent the complexity of SRL actions

	Vazquez et al., 2018)				
S13	An Innovative Multi-Layer Gamification Framework for Improved STEM Learning Experience (Zhao et al., 2022)	2022	no, teachers manually configure content	xAPI	N-EGM model, a gamification framework for future LMSs. gamification is effective in improving students 'engagement
S14	Standards for the Integration of Online Laboratories With Learning Management Systems (Ruano et al., 2023)	2023	no	xAPI	Standards for the Integration of Online Laboratories. In practice the use of xAPI standards were low by the teachers due to the learning curve and xAPI profile limitations.
S15	Using game learning analytics for	2018	no	xAPI	describes the methodology and main outcomes of the case

	validating the design of a learning game for adults with intellectual disabilities(Cano et al., 2018)				study to validate a game design. Effective tool for all types of learners, the main difference between Higher achievers and lower achievers is the completion time.
S16	Predicting students' knowledge after playing a serious game based on learning analytics data: A case study (Alonso-Fernández et al., 2020)	2020	Two types of models were created: linear models to predict exact score in range (0â€“15), and classification models to predict pass/fail category	xAPI-SG	predict student performance from xAPI data. Can predict performance with high accuracy.
S17	Radiology resident assessment	2018	no	xAPI	provides real-time feedback to residents using various

	and feedback dashboard (Durojaiye et al., 2018)				assessment metrics derived from multiple data sources. Both residents and the program director can monitor and evaluate progression toward training milestones.
S18	Enriching context descriptions for enhanced LA scalability: a case study (Samuelsen et al., 2021)	2021	no	xAPI	address the challenges of using xAPI learning context with regard to interoperability and data integration. Lack of clarity in how to describe context data in xAPI regarding interoperability and data integration. The recommendations relate to description/modelling of context in xAPI, data

					typing, validation, and documentation.
S19	Comprehensive Evaluations of Student Performance Estimation via Machine Learning (Mohammad et al., 2023)	2023	Several machine learning algorithms were used in this research to estimate student performance	Not used	Testing various performance datasets and machine learning algorithms to predict student performance. The CNN approach gives higher accuracy than all other TMLCs as well as their fusions. Secondly, the augmented datasets significantly improve performance accuracy
S20	Adaptive learning supported by learning analytics for student teachers'personalized training during	2022	no	xAPI	student's progress is also collected from their social interaction with other agents through different tools. The system that relies on the collection of data from all the tools and systems that are part of

	in-school practices (Fernández-Morante et al., 2021)	the learning process, not only from the LMS platform