Exploring the effect of AI-Facilitated Peer-to-Peer Support on Engagement, Grades and Pass rates: A Mixed Methods Case Study

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Declaration

I, Mark Wilson-Trollip, declare that the contents of this thesis represent my unaided work and that I have not previously submitted this thesis for academic examination toward any qualification. This thesis reflects my opinions, which may not necessarily align with those of the Cape Peninsula University of Technology.

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Signed: Date: 18 June 2024

ABSTRACT

This archival longitudinal case study explores the effect of artificial intelligence (AI) in facilitating AI peer-to-peer support and learning, focusing on how these dynamics affect engagement as part of a student belief system, grades and pass rates. The research employs a mixed-methods approach, integrating both quantitative and qualitative analyses. The qualitative component employs thematic reflexive and coded factor analysis to explore AI's peer-to-peer support learning effect on students' beliefs and perceptions. Through t-test, the quantitative aspect evaluates AI's effectiveness by comparing the grade performance of a cohort of students lectured using the AI platform and those lectured using traditional methods.

The thematic findings reveal a positive engagement response to the AI platform as it facilitates peer-to-peer learning support. High student response scores indicate a preference for using the AI-facilitated peer-to-peer support platform. T-test outcomes show limited statistically significant change (3-5% improvement) in academic grades following the platform's introduction across several financial management courses. Despite the positive student engagement perceptions of the platform regarding their grades, the peer-to-peer support platform did not lead to significant grade improvements. Implementing the AI platform showed a statistical improvement in the grades of one cohort of students; however, in Financial Management 4, notably, post-graduate students. The finding suggests an impact on grades, which, although not reaching conventional levels of statistical significance, cannot be disregarded. These findings show that engagement with the AI platform suggests a complex relationship between student engagement and academic achievement. Engagement is one component of student activity that improves overall student performance. Students have reported increased active learning experiences through this AI platform, which validates AI peer-to-peer support as an opportunity for institutions to provide additional academic student support. The three elements of traditional peer-to-peer support, exploring, enabling, and infusing, also promoted cognitive learning using this AI platform as peer-to-peer support. There is an increased activity for learning through this AI platform, further validating AI peer-to-peer support rather than encouraging students to remember. These insights add to the discussion on the efficacy of learning and teaching technologies, underscoring the difficulty in linking subjective engagement with objective performance metrics. The findings reveal that AI enhances student engagement and peer-to-peer support, fulfilling the objective of exploring its effect on engagement. However, the minimal improvement in grades suggests that engagement with the AI platform does not directly affect grade performance. The study recognises that AI peer-to-peer support platforms positively influence retention through enhanced engagement, aligning with understanding its impact on grades and pass rates. Recommendations highlight the need for personalised AI feedback and predictive AI to optimise student performance and retention. The study also notes limitations regarding controlling variables and implementing policies for AI-integrated learning environments. The study concludes that AI peer-to-peer support effectively enhances engagement and peer-to-peer interaction but requires further research to understand its full impact on academic performance. This research sets the stage for further exploration to conduct cross-cultural and longitudinal studies to assess AI's impact in varied learning and teaching settings and understand its sustained effect on learning outcomes. Further studies should include long-term data and qualitative evaluations to fully grasp the implications of AI-facilitated peer learning platforms on learning and teaching.

Keywords: Academic Achievement, Artificial Intelligence, Engagement, Personalisation and Individualised Learning, Personalised Learning, Peer-to-Peer support

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“Knowledge is power. Information is liberating. Education is the premise of progress in every society and family”. —Kofi Annan

CHAPTER 1 INTRODUCTION

The Artificial Intelligence (AI) learning and teaching market, with a valuation of USD 1.82 billion in 2021, is projected to experience a compounded yearly escalation of 36.0% from 2022 to 2030. Artificial Intelligence Technologies in Education (AITEd) have gained significant attention, resulting in research studies. Che et al. (2022) suggest further research to explore the field's various aspects despite this growth. This research identifies a persistent challenge in managing student progress, delivering personalised learning, student engagement and academic performance. Zhang (2020) alluded to this challenge, particularly within large class environments. “Little empirical evidence is available on what drives young people to engage in higher education… by showing that attitudes link to young people's intentions, and intentions subsequently associate with performance behavior. The findings provide guidance on how to foster students' grade performance” (Malmström & Öqvist, 2018pt.Abstract). Earlier, Popenici & Kerr (2017) stated that learning technology holds promise as a tool for improving individual learning and improving outcomes. Despite this potential, there remains a need for more consistency in its application and guidance for its design and implementation in learning and teaching settings (Cavanagh et al., 2020; Bhise, 2022).

This case study explores the effect of AI peer-to-peer support on student engagement, grades as part of achievement and performance, and as a mitigating factor in retention. Table 1-1 defines these operational definitions (additional detailed definitions follow in Chapter Two of the Literature Review).

Table 1-1 Operational Definitions

Operational Term	Operational Definition
AI Peer-to-Peer Support	Tools for peer learning include online forums, social networks, tutoring platforms, and collaborative software (Topping, 2005).
Grades as part of Achievement	Grade point average (Liu & Liu, 2000).
Student Engagement	It involves the level of interest, enthusiasm, concern, and hope students have when learning or being taught, including the desire to learn and

Operational Term	Operational Definition
	elevate their education level. In general terms, students learn better when they are curious, interested or motivated as opposed to when students are bored, indifferent, demotivated or in some other way disinterested; higher levels of student engagement or increased levels of student engagement are typical goals set by educators (Glossary and Great Schools Partnership, 2016). In many different contexts, however, student engagement may also mean how university leaders, lecturers or any other adults can 'engage' a learner more formally in the process of decision-making in university, in the process of shaping programs and learning activities (Glossary and Great Schools Partnership, 2016) and (Alrashidi et al., 2016).
Traditional Peer Support	The process involves individuals with shared experiences helping each other as equals (Zhao et al., 2021).

From the outset, the study does not advocate replacing human AI-facilitated peer-to-peer support. Still, the study assesses the possibility of using AI-facilitated peer-to-peer support to supplement the traditional peer-to-peer, face-to-face support structures that include all students, not only those at risk.

Most research in artificial intelligence grapples with a fundamental paradox: deep learning methods are inherently generalisable and capable of being applied across various domains due to the foundational principles of mathematics and algorithms. However, achieving proficiency in solving a specific task necessitates high-quality, accurately labelled data. This data, coupled with precise algorithmic strategies and optimal hyperparameter tuning, is crucial for tailoring models to perform well on particular applications. This paradox highlights the tension between the broad applicability of deep learning techniques and the need for specialised, well-annotated datasets to achieve task-specific accuracy. Deep learning is a machine learning algorithm that is the part of AI that improves the learning systems (Gupta, 2022). According to Moodley & Singh (2015), this attention to learning is because university departments will likely experience challenges managing students' academic work. There is a proposal to use AI as peer-to-peer support and measure levels of engagement, grade achievement and pass rates to prevent students from dropping out of courses (Lainjo, 2023). With the increased tendency towards learning outcomes and practices based on the student's learning preferences, attitudes and expectations are changing while the focus is on skills development. The increasing rate of technology and access to tools further emphasises the significance of AI in learning and teaching practices, as observed by Toksh et al. (2022). Kasnec et al. (2023) suggest large language models offer an advancement in AI for students and teachers. AI has significantly impacted various sectors, including healthcare and finance, where it has improved diagnoses, outcome predictions, and treatment identification, transforming practices in these areas (Russell, 2010).

The history of AI, theoretical perspectives and data privacy measures are integral to evaluating AI's influence and potential risks in learning and teaching.

1.1 The Problem

There is a shortage of knowledge concerning the potential of AI platforms to facilitate peer-to-peer support and influence student engagement, grades as achievement and pass rates as academic performance in a mass learning environment. There is a lack of knowledge on how AI influences students' participation and grades, which affects retention according to Tinto's (1975) & Bean's (1980) Retention and Attrition Theories. This research evaluates AI's influence as a machine peer-to-peer learning support tool.

Educators agree on the benefits of adaptive learning, but evidence-based research remains limited as the field of adaptive learning is still evolving within higher education (Liu et al., 2017). The lack of student engagement in online learning poses a problem (Hew & Huang, 2023). Hew & Huang (2023) suggest promoting active learning through the online flipped classroom model, promoting self-regulating skills and reducing the sense of isolation. A comprehensive analysis employing a mixed methods longitudinal case study seeks to bridge the knowledge gap significantly.

1.2 Significance

This study is significant as it addresses the existing knowledge gap regarding the potential of AI platforms to facilitate peer-to-peer support and influence student engagement, grades, and pass rates in mass learning environments. Despite growing recognition of the benefits of adaptive learning, there is limited evidence-based research on how AI impacts student participation, academic achievement, and retention. By drawing on foundational theories like Tinto's Retention Theory and Bean's Attrition Theory, this research evaluates the effectiveness of AI as a peer-to-peer learning support tool. The study's comprehensive analysis aims to clarify AI's role in enhancing student outcomes and provide insights into how AI-driven platforms can balance the need for personalised learning with the scalability required in modern educational settings.

The study draws on seminal theoretical frameworks from (Tinto, 1975; Bean, 1980; Bork, 2002; Tight, 2019; Rowe et al., 2022). The study explores the complexities of adapting traditional peer tutoring—a method yielding mixed results in past studies—and explores the potential of AI to enhance peer-to-machine learning (Greenwood, 2019). It integrates blockchain technology with peer-to-peer tutoring to analyse its influence on engagement, grade achievement, and the potential effect on retention. The study intends to examine and classify the influence of AI peer-to-peer platform support on student perceptions, academic grade achievement, and pass rates as a tool for facilitating personalised learning. It does not propose establishing definitive predictions but explaining new phenomena and impacts (Eisner, 2017)[1]. Personalised learning, tailored to the individual's pace, style, and needs, contrasts with the collective nature of peer-to-peer support. There needs to be more clarity between the feasibility of mass learning and teaching and the growing need for individualised instruction. This conflict underscores the need to balance the benefits of individualised learning and teaching with the practical challenges of implementing such a system (Minn, 2022).

With the learning platform, this interdependence between personalised learning and peer-to-peer support, rather than being at odds, may boost academic performance and engagement. The complementary roles of AI in mediating peer-to-peer support to align with personalised learning goals counters the notion of inherent contradiction, instead showing a harmonious blend that elevates the learning and teaching experience. Through this approach, the research aims to identify the impact of AI-assisted peer-to-peer support platforms and their contribution to individualised learning and teaching outcomes. Greenwood (2019) has observed that peer tutoring's efficacy varies across learning and teaching contexts, necessitating an alternative adaptive instructional approach. This adaption method explores AI's influencing role as a learning and teaching method to facilitate peer-to-peer learning, aligning with current learning and teaching needs that affect student engagement and academic performance.

1 “The options available are multiple. We can decide not only what to use but how to prepare what we decide to use. How shall the vegetables be sliced? What proportion of each ingredient should be included? How should it be arranged?” (Eisner, 2017: 18).

1.3 Aim and Research Questions

This study aims to outline how an implemented AI platform may influence student engagement, grades, and pass rates as part of academic achievement, promoting learner progression by assisting students in returning to higher education. It questions how AI, as a peer-to-peer support machine mechanism, can contribute to resolving the contradiction between the scalability of educational delivery and the necessity for personalised learning experiences. The study supports Kem's (2022) view by examining the AI interactive platform Connect® for its efficacy in facilitating personalised learning environments, an essential peer-to-peer support component. Connect®, an interactive learning technology platform, is a learning and teaching tool that purports to improve student outcomes and streamline course management. Such claims through research or evaluations may demonstrate its effectiveness in improving student achievement and experiences.

This study aims to bridge the gap between the potential and practice of AI peer-to-peer support in education. It examines the effectiveness of an AI peer-to-peer platform in influencing student engagement and grades. Additionally, it explores how this technology can enhance learning context, persistence, and completion rates. It discusses how using AI in peer-to-peer support can enhance academic achievement and performance to improve the dropout problem. While AI can potentially revolutionise the learning and teaching process, the following questions arise regarding its efficiency. The research questions in Table 1-2 measure the AI platform's effectiveness in student engagement, grades, and pass rates and its role in facilitating peer-to-peer learning.

Table 1-2 Research Questions and Objectives

MQ: To what extent does Peer-to-Peer AI support influence student engagement, grades, and pass rates?	
Sub-questions	**Objective**
RQ1: How do students perceive the influence of AI-facilitated peer-to-peer support on engagement as part of their belief system?	To understand how such systems influence their engagement and overall learning experience, Tinto’s (1975) Retention Theory and the Theory of Attrition (Bean, 1980).
RQ2: To what extent does AI-facilitated peer-to-peer support enhance student	To what extent does AI peer-to-peer support influence grades as a component of the Tinto (1975) Retention Theory and the Theory of Attrition (Bean, 1980).

MQ: To what extent does Peer-to-Peer AI support influence student engagement, grades, and pass rates?	
Sub-questions	**Objective**
grades by assisting students in their return?	
RQ3: To what extent does AI-facilitated peer-to-peer support influence pass rates?	To what extent does AI peer-to-peer support influence pass rates, a component of the Tinto (1975) Retention Theory and the Theory of Attrition (Bean, 1980).

Table 1-2 outlines the research objectives by statistically analysing student data extracted from records and whether AI-assisted platforms' functionality facilitates peer-to-peer support and influences student engagement, grades, and pass rates as a subset of performance. This alignment aids in framing the research questions within established theoretical contexts.

Table 1-3 Aims and Related Activities

Aims	Activities
Engagement as part of a Student Belief System. To explore engagement as a broader student belief system towards AI peer platforms.	Analyse and interpret past student surveys and activity levels using the student management system data.
Grades as part of Academic achievement. To compare grades by students obtained between traditional face-to-face instruction and an AI peer platform.	Compare grade data on academic performance pre-and post-intervention.
Pass rates as part of performance. Evaluate how AI peer-to-peer support platforms affect pass rates compared to pass rates of traditional teaching methods.	Analyse and interpret past student academic pass rate results.

Table 1-3 summarises the aims and activities of the study to explore and evaluate the impact of AI peer-to-peer support platforms on academic achievement and student belief systems, comparing traditional teaching methods and AI platforms and analysing past student surveys and activity levels. Eisner (2017, p.33) said a qualitative study is "nonmanipulative, that is, it tends to study situations and objects intact, and it is naturalistic". This study uses archival surveys as its source of data instrument, maintaining its natural form. Further, he said an investigation must relate “to the self as an instrument” (Eisner, 2017: 33). “The self is the instrument that engages and makes sense of the situation. This is often done without an observation schedule” (Eisner, 2017: 34).

In alignment with the research questions and the natural state of the data, the broader effect of AI assistance as peer-to-peer support on academic achievement and student retention underpins this research. Figure 1-1 presents theories and fields related to the research questions.

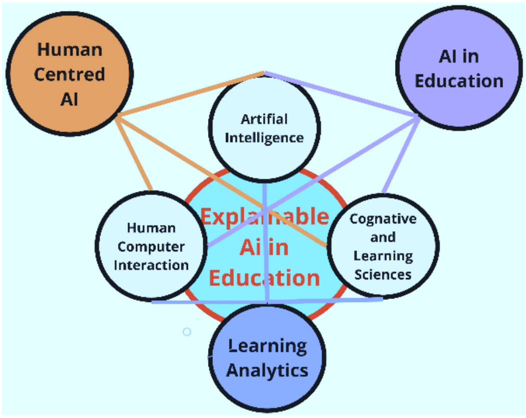

Figure 1-1 Related Fields (Khosravi et al., 2022)

It is necessary to integrate each field in Figure 1-1 thoughtfully and relate these to the research questions:

- Artificial Intelligence: The research examines how AI technologies influence peer-to-peer learning. Additional research questions may include: What AI methodologies most effectively identify and match peer learning partners?
- AI in learning and teaching expands the research to consider AI’s role in learning and teaching settings. Relevant questions might be: What AI features impact traditional teaching methods in learning and teaching environments?
- Cognitive and Learning Sciences: Integrating cognitive theories and learning sciences can generate questions like, what cognitive principles are essential for AI to facilitate peer learning effectively?
- Explainable AI in learning and teaching: Given the importance of trust and understanding in learning and teaching tools, the research could explore the following questions: When can explainable AI improve teacher and student acceptance of AI-facilitated peer learning?

- Human-Computer Interaction (HCI): This domain can shape research questions focused on user experience, such as: When does the interface design of AI tools affect student engagement in peer learning?
- Human-Centred AI: This overarching theme can guide questions of ethics and design. What human-centred principles must be integrated into AI to enhance peer-to-peer learning and teaching experiences?
- Learning Analytics: Learning and teaching data analysis may prompt questions like: What learning analytics measure AI-facilitated peer learning's effectiveness?

This study explores AI as a facilitator of peer-to-peer support through the focus areas of student engagement as part of their belief system, grades as part of achievement and pass rates as part of performance illustrated in Table 1-4.

Table 1-4 Primary Areas of Focus

Primary Areas of Focus	Details
AI peer-to-peer support could influence engagement, grades and pass rates.	Explore these aspects to gain deeper insights and assess how effectively AI-assisted platforms facilitate and influence traditional peer support. These aspects include interpreting and statistically analysing students' perception of the AI platform, which influences their engagement, grades, pass rates, and its indirect impact on retention.

It measures AI peer-to-peer support's efficacy in engaging students by analysing their grades, experiences, and perceived beliefs to their expectations. This study focuses on elements of peer-to-peer support by examining the supposed effectiveness of AI peer-related human-like interactions. The study aims to uncover what affects students' attitudes and relations with AI peer platforms, applying their views as possible learning frameworks. Therefore, this research seeks to advance the knowledge of AI opportunities and challenges in today's learning environment.

Examining the hidden design affordances of the AI platform forms a pattern that considers technology, user interactions, compatibility with cognitive mechanisms, analysis, and humanism. This layout is a holistic view of the subject where AI potentially benefits learning and teaching with the technological factor that defines it with the human factor in education.

1.4 Possible Teaching Benefits of AI Peer Platforms

The study investigates the effects of implementing AI peer platforms on learning outcomes and students' participation within a blended learning context that directly informs learning policies and procedures (Shin, 2021). The effects of these have implications for student success, and institutions must ensure they comprehend them fully (Mattas, 2023). This study potentially provides valuable data concerning the advantages of adopting AI peer platforms in learning environments (Zhao et al., 2021). Thus, it is possible to create intelligent learning ecosystems in universities using the parameters of student satisfaction, faculty support, utility, and competitiveness. It is helpful to have such conclusions, bearing in mind that with the introduction of AI, its effects on education have also risen. Therefore, integrating AI peer and hybrid learning platforms can help the institution improve its performance and assist students in the learning process. Higher learning facilities can also assist in increasing superior learning facilities by assessing the student's impressions of technological advancement, nurturing the distinctiveness of the instructional aids, and optimising the students' blend delivery (Ali et al., 2023).

AI peer platforms potentially benefit students because they bring in new strategies that help develop creativity and critical thinking skills (Einstein, 2023). The presence of these platforms requires a clear and detailed plan regarding academic achievement, level of activity, and thinking abilities (Børte et al., 2023). For reference, the student academic achievement factor has sociological and economic implications for the future of education and the use of AI and peer learning. The learning experience should concentrate on ethics, revenue generation, and teaching efficiency. Enhancing student retention, achievement, and engagement means an integrated approach to students' education contributes to formulating strategy and policy (Sadeghi et al., 2014). Tlili et al. (2023) agree with the above claim, stating that AI can only augment learning and performance when the teaching and learning process involves AI cooperation. Lecturers may consider adopting AI peer-to-peer support to increase learners' engagement and performance, potentially benefitting retention rates.

Meeting this challenge requires creating learning and teaching support tools focused on AI, and this direction is quite promising when it comes to enhancing learning outcomes. Traditional peer support and engagement (as part of a student's belief system) encompass the conventional ways students help each other without AI intervention (Maheady, 1998). At the same time, academic performance indicates the measurable outcomes, like grades and pass rates, of student learning. According to Diaz Lema et al. (2023), AI brings the prospects of enhancing learning environments that are more sensitive to students' needs for better learning. Considering the elements of peer-to-machine learning with AI implies that AI systems should bolster or supplement the students' belief systems and enhance their grades. Machines may facilitate it. The term student belief system encompasses students' convictions and attitudes. These beliefs relate to their perceived ability to succeed academically.

Implementing such systems raises obstacles, including the need for domain-specific adaptations and the balance between mass education strategies and personalised instruction demands. Challenges arise due to the conversion of a face-to-face idea to meet individual learning requirements (Elibol & Bozkurt, 2023). These remarks prompted the following query: what about other activities, such as AI peer-to-peer support, that might support learning and teaching?

Kem (2022, pp.385–391) sees AI as "a rather promising space and an instrument for enhancing students' performance in learning".

1.5 Background

Over time, AI has experienced considerable development, characterised by progressive advancements, with key figures and pivotal milestones significantly shaping its evolution. However, there is a need for a deeper understanding of this progress and its implications (Cooper, 2023). The first slow progress in AI, from Babbage's 1884 work to the early 1960s, can be attributed to limitations in computing power, which restricted the development of advanced AI systems (Mijwel, 2015; Haenlein & Kaplan, 2019).

The rise of AI in research has led to the exploration of principal issues, such as the effectiveness of technology in shaping successful learning paths through data analysis (Norvig & Intelligence, 2002). The problem has remained in translating research findings into practical applications that enhance learning achievements and supply affordable, customised learning experiences (Adiguzel et al., 2023; Cooper, 2023). Another challenge lies in balancing the feasibility of mass learning and teaching with the costs associated with personalised learning and teaching (Nechita et al., 2023). Implementing individualised learning environments is still a difficult task in which face-to-face interaction with the learners is often limited (Hadjar et al., 2023). Culturally and ethically related issues like bias, prejudice, privacy, and the right to freedom also act as barriers when implementing AI systems in education (Chew et al., 2017).

Exploring AI’s history, perspectives, trends, and focus areas is necessary to fully understand AI's potential in learning and teaching and address primary challenges (Haenlein & Kaplan, 2019). A multidisciplinary approach is required, integrating insights from computer science, psychology, education, and other relevant fields (Calvo & D’Mello, 2010).

1.5.1 Learning and Teaching with AI-Assistance

Addressing the issues of engagement, performance, and peer-to-peer support in institutions is crucial due to their complex nature and wide-ranging consequences. Predictive artificial interactive models offer a promising approach to mitigating this challenge, potentially reducing its social and economic impacts (Del Bonifro, 2020).

In South Africa (SA), the graduation rates are significantly low, with only 15% of students completing their studies, according to the National Plan for Higher Education (NPHE). Letseka & Maile (2008) report that initiatives were underway to improve graduation rates among African students and promote diversity in academic and administrative roles, particularly at higher levels. Further to the SA context, “ Although the general perspective is that higher institutions in South Africa are not yet ready for digital learning due to the availability of infrastructure, many practices toward digital learning are being implemented. There are high hopes to believe in well-implemented digital learning Universities in the next decades”(Bakama et al., 2022sec.Abstract). Schoeman & Naidoo (2023sec.Abstract), in a conference paper, suggests, “The Fourth Industrial Revolution (the 4IR) will have a continuing impact on our daily lives. Currently, the depth and breadth of the 4IR are unknown quantities. However, what is known is that all stakeholders, including academia, need to work together to “shape the future” (Schwab & Lew-Williams, 2016)”. Therefore, Higher Education Institutes (HEIs) must re-think, re-imagine, and re-create how they conduct teaching and learning. The South African president established a commission recommending how South Africa would respond to the 4IR in 2018. In 2020, the Presidential Commission on the Fourth Industrial Revolution (PC4IR) published its recommendations. One of the aspects highlighted was the role of HEIs in responding to the 4IR. In particular, the need for graduates to be familiar with and use 4IR disruptive technologies, such as artificial intelligence (AI), was highlighted.

While much of the recent research has centred on the role of artificial intelligence (AI) in education, particularly in response to the challenges posed by COVID-19, there has been limited focus on AI's potential as a tool for peer support in learning environments. The pandemic highlighted the urgent need for digital solutions to bridge educational gaps, but this focus has primarily addressed immediate, short-term needs. Consequently, the exploration of AI as a facilitator of peer-to-peer learning, which could enhance student engagement and retention in the long term, remains underdeveloped. This gap presents a critical opportunity for further investigation, particularly within the context of South Africa's higher education system, where innovative approaches to student support are essential. The consequences of high student dropout rates extend beyond individual students (Copeland, 2023). They also burden university staff with increased workloads and hinder research opportunities (Hostler, 2023). Such a situation depletes resources and diminishes student enrolment and research outputs, especially in postgraduate studies (Spowart et al., 2019). Therefore, it is crucial to understand the causes of high dropout rates and develop effective strategies to address them (Styger et al., 2015).

Given the role of academic support and funding deficits, university departments could coordinate multifaceted peer support strategies to improve engagement and performance. They could integrate AI platforms with traditional support programs for segments that experience high failure rates and other segments of student learning.

1.5.2 AI-Facilitated Peer-to-Peer Support, Engagement, Grades and Pass Rates

Some of the challenges of learning and teaching using AI as peer-to-peer support involve extending the use of AI and generalising its usage towards improving the opportunity to offer students a unique learning experience (Hariram et al., 2023). In an Intelligent Tutoring System (ITS) context, the AI architecture should provide flexibility in its functionality with the learning environment and user activity that takes place within the design of ITS (Sandmann et al., 2008).

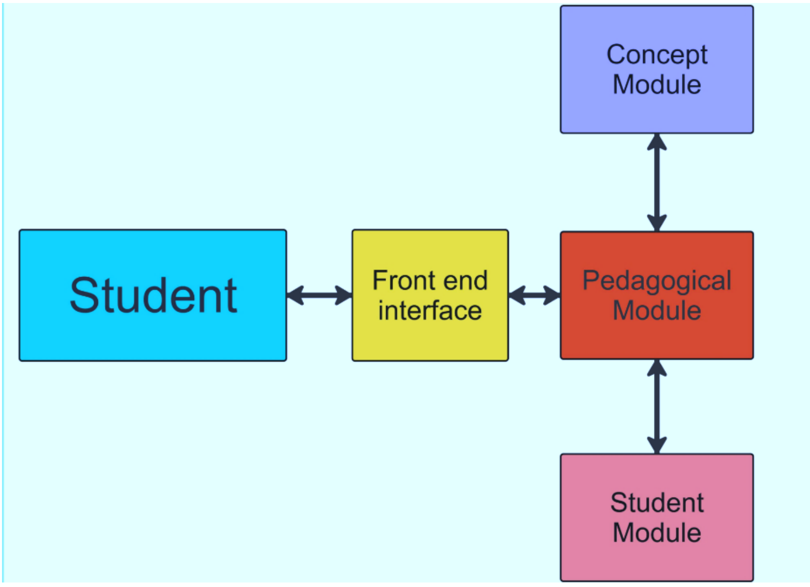

Figure 1-2 Architecture of Intelligent Tutoring System (ITS) (Salman, 2013)

Figure 1-2, presented by Salman (2013), represents the architecture of a learning and teaching system consisting of four interconnected components, thereby advancing personalised learning:

- Front-end Interface: The user interface is where students interact with the system, presenting learning material and collecting user inputs.
- Pedagogical Module: The instructional component decides the teaching strategy. It uses information from the concept model and student module to tailor the instructional approach.
- Concept Module: This module houses the subject matter or knowledge base. It contains the interactive concepts and facts the system aims to teach.
- Student Module: It tracks and models individual student progress, performance, and learning styles. This adaptive component aims to personalise the learning experience.

This study examines the influence of the AI facilitator database of peer-to-peer support within the ITS model on engagement and grade achievement, as illustrated in Figure 1-3. Information flows from the concept model and student module to the pedagogical module, indicating that the content and student understanding inform teaching strategies. The pedagogical module then influences the front-end interface, indicating that the teaching strategies determine the instructional content delivered to the student through the interface.

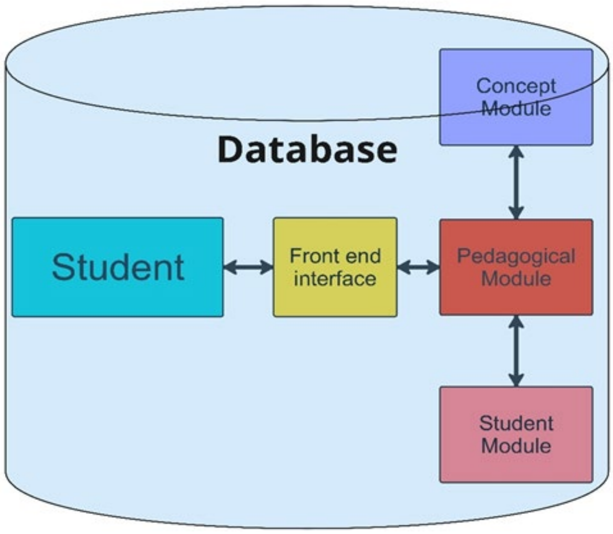

Figure 1-3 Adaption of ITS Model (Salman, 2013)

The student interacts with the front-end interface, which informs the student module. All modules interface with the peer-to-peer support facilitator, closing the loop.

1.5.2.1 Peer-to-Peer Support

Institutions should prioritise enhancing eLearning peer-to-peer support experiences (Cooper, 2023). Incorporating eLearning as peer-to-peer support poses several difficulties, according to Elbanna & Armstrong (2023). A few of these are the accessibility and appropriateness of digital resources, the technological proficiency of lecturers, the use of inexperienced parents as teachers, erratic internet access, and the institutional decision to embrace or reject blended learning strategies (Zawacki-Richter et al., 2019; Gates, 2015; Mushfi El Bali, 2022). Various factors could hamper the efficient performance of eLearning peer-to-peer support activities (Alenezi et al., 2023). Another approach is enrolling students in eLearning programs, but they need help finding suitable courses or programs in their preferred language (Alenezi et al., 2023). These complex issues underscore the importance of comprehensive exploration of learning systems and their potential to address the limitations and challenges present in current learning and teaching settings (Rizvi, 2023). Such a complex strategy can help moderate student academic load management(Moodley & Singh, 2015).

1.5.2.2 Engagement

To solve the current research questions, exploring how AI might interact with students is pertinent to increase the desired engagement, dynamism, motivation level and overall knowledge retention in the long term (Maharaj, 2018; Cockburn et al., 2018). When considering some of these research objectives, it is possible to gain a better insight into the strengths and limitations of AI and help in maximising its potential to improve the learning-teaching process and create an environment that will incorporate change and flexibility while at the same time establishing functional and efficient working models. Frameworks for learning systems have attracted much attention due to their ability to present customised learning interfaces (Chen et al., 2023). The effectiveness of these methodologies compared to traditional forms of instruction and the ongoing process of perfecting their execution has yet to be discovered by researchers (Tlili et al., 2023).

As Huang *et al.* (2023) stated, calculating the frequency level of students' engagement depends on the information collected from the Learner Management System. The quantitative features include the total number of learning materials viewed by the students, the number of messages or posts, the corresponding responses in the forums created, and the number of specific tasks accomplished by the students. The time-related aspect is more or less limited to the days the students are online with the course (Hsiao et al., 2019).

To determine to what extent academic achievement changes by implementing AI peer-to-peer support depends on the following factors: student engagement which means students' participation in academic processes and their adherence to the university values and policies, academic self-efficacy, which means the belief of the students in their ability to achieve academic success, and academic motivation which means the drive of the students to enhance their grades and pass rates (Dogan, 2015).

1.5.2.3 Grades and Pass Rates

Investigation is required to determine whether artificial intelligence can enhance academic grade performance (Spurlock, 2023). Academic grade performance for purposes of this study is grade achievement. Performance may include other factors, like attitudes, "attitudes link to young people's intentions, and intentions subsequently associate with performance behavior" (Malmström & Öqvist, 2018: Abstract). Research indicates that individualised instruction can result in improved learning outcomes, grades, and higher retention rates (Bork, 1999; Holmes, 2023). Leveraging AI as student peers in learning and teaching have faced implementation challenges in promoting a learning culture and the Student Learning Models (SLM), which seek to personalise learning, making it unique and responsive to the student. Integrating AI to realise how it can formulate individualised instruction for large groups of students remains vital.

Research should find a multifaceted approach for incorporating AI into learning and teaching environments (Faqihi & Miah, 2023).

1.5.3 A Multifaceted Approach

The research will qualitatively and predominantly quantitatively investigate the effect of an AI peer platform on student engagement and grades as a performance measure of success. This study seeks to contribute to the existing knowledge on learning platforms by using various data collection techniques and analysing historical academic records and student surveys. The findings of this study seek to inform strategies for implementing AI peer platforms to support students in enhancing teaching and learning processes.

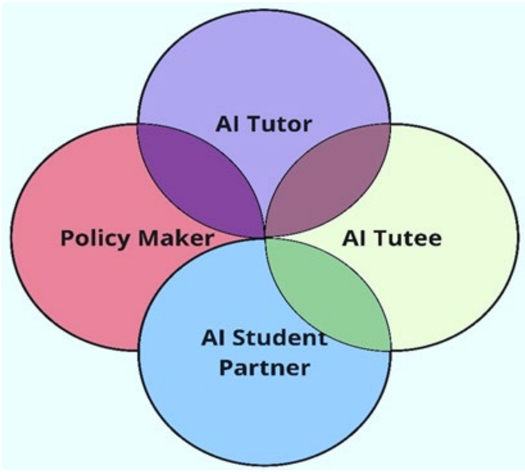

Figure 1-4 Framework for the Role of Peer Platforms (Guthrie, 2023)

In the real world, it is essential to explore the influential support roles that AI-assisted platforms, as peer-to-peer support, should fulfil in learning and teaching contexts, including that of AI tutor, AI tutee, AI learning partner, and policy-making advisor, as shown in Figure 1-4. The adapted Guthrie (2023) illustration suggests in Figure 1-4 that AI tutoring should incorporate human tutoring, personalised learning methods, and approval procedures, all proven to enhance learning outcomes.

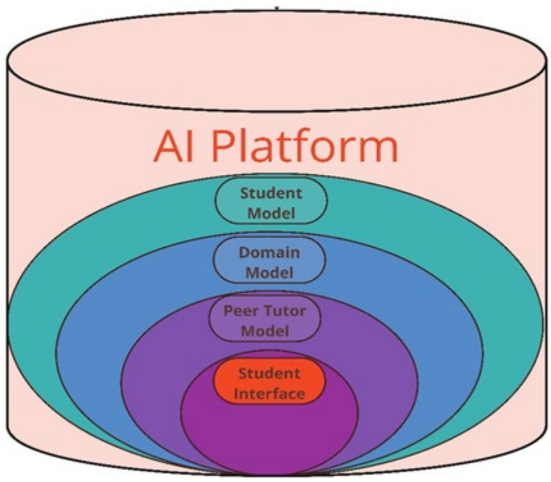

Figure 1-5. Components of an Intelligent Tutoring System (Sottilare, 2018)

Earlier research indicates that intelligent tutoring systems work efficiently at increasing learning results (Sottilare, 2018). Figure 1-5 illustrates the inclusion of the AI platform in the intelligent tutoring system.

In the AI tutee role, students assume the role of tutors to improve academically. The AI platform aligns with constructivist theories as a tool for student-centred teaching and learning (Von Glasersfeld, 2012). It encourages critical thinking and complicated thinking processes while helping students obtain and assess data (Shah Ph & Kumar, 2019). AI peer platforms can assist in creating and evaluating lecturer guidelines, providing a comprehensive understanding of both issues and benefits (Chassignol, 2018). The study undertakes this multifaceted approach under the guidance of earlier theoretical perspectives.

1.6 Theoretical Perspectives

The research strategy used in this study combines several crucial theories and viewpoints to analyse factors that determine the reception and efficiency of AI as peer-to-peer support. This combination of views tackles theoretical frameworks and their implementation to gain a deeper perspective into AI with its core focus on education.

Spady's (1970) findings highlight the importance of students' relationships with their learning environments, particularly regarding retention. Several aspects get in the way of the learning process: academic performance, cultural expectations, learning outcomes, creativity, attitude formation, and help from peers (Foschi, 2023; Malmström & Öqvist, 2018). Integrating Spady's (1970), Tinto's (1975) and Bean's (1980) retention and attrition theories provides a complete framework of student performance and ability, attrition and retention (Swail, 2006; Van der

Meer et al., 2017; Tight, 2019; Figueira, 2015). Ability comprises factors like academic performance, friends' help, parents' experience, and intelligence (Khalil & Elkhider, 2016). Tinto (2017) supplements this view with intellectual capability and replaces the 'failure and success' approach with the ongoing changes influencing students' progress incorporating institutional sociocultural systems proposed by (Bean, 1988). From Bean's (1988) study, student interactions and background characteristics could put students in shape on how best to accustom themselves to the new learning environment. From this point of view, one can state that students' orientations and practices significantly impact Bean & Metzner's (1985) desire to continue their studies.

Bork's (1999) synthesis positions emphasise that the AI application potential is not restricted to specific sectors of society but rather engulfs all spheres of life, education and learning especially. It highlights the increased capability and efficiency of using AI across industries such as banking and healthcare systems. It presents how to enhance teaching and learning by incorporating AI technology (Abgaryan et al., 2023).

These professional pointers and perspectives are invaluable in enhancing the implementation of artificial intelligence in a learning environment that fosters peer learning. From it, Kerby (2015) emphasises the need to understand the variables that underlie engagement and success and recognise institutional and individual student personality factors. Students are exploring the benefits of integrating AI in educational institutions, challenging the effectiveness of peer-support and AI peer drivers on academic performance and students' belief systems (Rodriguez et al., 2022). This study addresses how AI technology can enhance peer-to-peer support for learning in a mass educational environment.

Thus, student retention remains a multifaceted problem in the processes of educational function, acknowledged as a significant and highly raising issue, which offers multiple challenges for proper solutions in the context of educational organisations (Reason & Braxton, 2023). It has long been a concern due to its impact on both academic and financial aspects (Aljohani, 2016). To address this problem, researchers have developed theoretical frameworks to understand and mitigate factors contributing to student dropout (Ardawi, 2022). These frameworks actively discuss their role in student achievement, engagement, peer mentoring and retention and identify potential enhancement strategies (Tight, 2019). Various research and theoretical frameworks, such as those proposed by Tinto (1975) & Bean (1981), have explored this issue (Guerrero, 2023). However, the question remains: What machine learning factors influence academic success and engagement in learning and teaching settings (Jama et al., 2009)[2]?

Nicoletti & de Oliveira (2020), revisiting Tinto's (1975) “Model of Institutional Departure”, emphasises the importance of integrating students into both formal aspects (achievement, relationships with teachers and staff) and informal elements (peer-group interactions, extracurricular activities) of learning and teaching and social systems to ensure successful student retention. Kerby (2015) extends Tinto's (1975) model by incorporating elements such as internal culture and environment, external forces, and students’ sense of belonging (Dužević et al., 2018). According to Kerby (2015), institutions must create a supportive environment that develops learning and adjustment for students to thrive and remain in their learning programs (Fan et al., 2023). The absence of human contact in AI-driven learning platforms might limit social learning opportunities and the emotional support that peers and instructors provide—a human interface fosters motivation and engagement within learning environments.

The actual value of AI lies in its capacity to provide personalised feedback and customised learning trajectories. This way, delivering more efficient and precisely tailored education to cater to different students' learning requirements becomes easier. These approaches enhance student participation, impact academic outcomes positively, and increase the learner’s retention level (Li & Xue, 2023).

Although theories concerning the student retention concept help to see the students’ characteristics, they cannot cover the whole spectrum of individuality (Pedler *et al.*, 2022). Subsequent research should integrate new facets to elaborate the theoretical framework that defines reality with maximum precision (Winkelmes et al., 2023).

AI aims to renew the learning and teaching environment to improve student results, fill the gaps in retention theories, and develop new approaches to analysing student performance and retention as peer-to-peer support providers. Participation rates among students increase as AI

2 Data Mining (DM) is a promising strategy for enhancing academic performance and retention, alongside diversity, equality, and inclusion (DEI) initiatives in higher education institutions and intervention programs to address student dropout.

approaches are used in learning practices to assist teachers in recognising various aspects of learners' behaviour.

In the sub-sections that follow, a discussion addresses AI-facilitated Peer-to-Peer Support (1.6.1), Engagement (1.6.2) and Grades and Pass Rates (1.6.3).

1.6.1 Peer-to-Peer Support

Research demonstrates that peer mentoring promotes student success, especially within vulnerable learning groups (Ross & Cameron, 2007; Shantini et al., 2023). Terrion and Leonard (2007) demonstrate that integrating mentoring programs into university student support services improves academic achievement and reduces dropout rates. Further investigation is needed, however, to understand the correlation between peer-to-peer support functions and the most suitable type of support for diverse needs (Williams & Reddy 2016), illustrated in Figure 1-6.

Figure 1-6 Mentoring Methods (Williams & Reddy, 2016)

As a significant strategy of learning that takes advantage of students' mutual interaction to improve their knowledge, engagement and success rates, there is a need to develop and evaluate Peer Assisted Learning (PAL) interventions as one of the approaches to teaching and learning (Chapman, 1998; Balilah et al., 2020; Weitekamp et al., 2020). Topping & Ehly (1998) support students in encouraging each other in the learning process, including group cooperation and problem-solving. PAL is necessary for developing student-centred learning through interaction (Balilah et al., 2020).

Improving the PAL systems' effectiveness requires identifying how peers' interpersonal interaction affects learning (Williams & Reddy, 2016). Although individual coaching may offer unique solutions to academic enhancement, students point out that the high costs of the strategy make its application inconceivable (Kumar et al., 2023).

Currently, there are various student development theories, which means that by incorporating such innovative elements as AI, one can design valuable strategies that would fit different students from different backgrounds. These AI-facilitated peer-to-peer support platform approaches may build upon the paradigms established in traditional frameworks while utilising the latest technology as a tool to cater to a diverse set of learners. The integration of the classic paradigms and the advanced approaches enhances the interrelated establishment of the ideal methods of education that enhance students' diversely complex experiences. Specifically, targeted academic and career development coaching forms have increased retention and improved the student's personal and academic development (Campbell & Campbell, 1997; Dunn & Herron, 2023). Louis & Freeman Jr (2018) also note in their literature that such individualised programs may reach a particular population of students or a specific type of student. They can improve retention, self-assurance, and success rates (Campbell & Campbell, 1997).

Mentoring refers to a twofold partnership where one individual assists another in fulfilling one of the primary human needs more effectively (Wiesman & Forestal, 2006). It can be inter-student tutoring, faculty-student tutoring, staff tutoring, and AI student tutoring (Dunn & Herron, 2023). Peer-assisted learning (PAL) uses peer interactivity to support student-centred learning, encouraging overall personal growth and motivation for success (Rohrbeck et al., 2003).

Just like the global positioning system navigates the car through the country by providing an option route, direction, information, efficient tracking and encouragement, the mentor navigates the student's academic trip. They empower students to navigate successfully, address learning challenges and accommodate individual learning styles and comprehension levels (Crisp, 2010; Colvin & Ashman, 2010). Effective mentoring incorporates three key elements: exploring (drawing out the mentee's prior knowledge), enabling (guiding the mentee to refine their understanding), and infusing (supplying added information as needed), thereby promoting cognitive learning in mentees (Bowman-Perrott et al., 2023). These elements are potentially available in AI-assisted peer-to-peer support platforms.

However, power dynamics, control, dependency, and intimacy are often overlooked in mentoring, learning and teaching discussions, highlighting the need for further research (Janssen et al., 2016). Such investigations can contribute to developing ethically sound, engaging AI mentoring and peer-to-peer support practices (Hale, 2000).

1.6.2 Engagement as Part of a Student Belief System

Song & Kim (2021) suggest the analysis of learning and cognitive processes requires a conscious awareness and appreciation of students' attitudes and levels of participation. Schommer-Aikins (2012) states that a belief system umbrella comprises two significant components: Standards for involvement and encouragement. Mental characteristics refer to faith, emotion, and perceived cultures, influencing students' experiences and learning. They all provide each of the students with a unique learning context that determines motivation, complicity, and learners' achievement, according to (Serrano et al., 2019).

Thus, the success factor of applying AI assistance for effective learning engagement depends on the availability of AI integration in learning processes and instruction development. It is crucial to understand how integration occurs alongside the usage of teaching practices and how it caters to the unique learning styles of every learner (MacDowell & Lock, 2023; Al Mamun et al., 2020). Through ILEs, AI can influence students' mental and emotional status prospects and directly offer Personalised assistance that supports beliefs and academic performance (Bahari, 2023). The place of engagement and the choice of devices to access the AI system influenced student engagement (Alzahrani, 2023).

The Self-Determination Theory (SDT) emphasises the strong connection between student engagement and motivation in achieving academic goals (Areepattamannil et al., 2023). SDT, as defined by Gagné & Deci (2005: 335), "ranges from a motivation, which is lacking in self-determination, to intrinsic motivation, which is invariantly self-determined. Between motivation and intrinsic motivation, along this descriptive continuum, are the four types of extrinsic motivation, with external being the most controlled (and thus the least self-determined) type of extrinsic motivation, and introjected, identified, and integrated being progressively more self-determined". SDT "provides a fuller and more useful approach to understanding the motivational bases" (Gagné & Deci 2005: 356). It underscores the need to understand the factors that influence motivation and engagement, particularly the structural components of the classroom environment (Rohrbeck et al., 2003). Various course delivery modes can perfect student motivation and achievement, including web-based instruction, blended learning, video streaming, recorded streaming, active learning technologies, and in-person instruction (Wentzel & Wigfield, 1998; Spurlock, 2023).

AI-powered platforms may transform peer-to-peer support and traditional teaching, as Figure 1-6 illustrates the mentoring matrix for learning (Ryan & Vansteenkiste, 2023). These platforms can assess a student's belief system, track progress, and offer personalised learning experiences, such as the Cognitive Tutor offered by Carnegie Learning (Weitekamp et al., 2020). However, concerns exist about over-reliance on technology and the importance of keeping a balance with human interaction (Glikson, 2020). One approach potentially supporting AI as a peer-to-peer support facilitator is the flipped classroom approach. AI peer-to-peer support systems present promising techniques for enhancing learning outcomes by increasing student motivation and engagement (Huang et al., 2023). The discussion of the flipped classroom approach appears later in Figure 2-14. The traditional peer mentoring and tutoring paradigm supports this technique.

1.6.3 Grades and Pass Rates

Recognising students who can effectively manage the diverse academic demands currently facing higher education institutions is a pressing concern (Baashar, 2022). The National Centre for Education underscores the special attrition rate by reporting that around a third of first-year university undergraduates discontinue their studies after their initial year (Hutson, 2022). This discontinuation of studies underscores the urgent need to effectively use AI to enhance overall academic achievement (Hutson, 2022).

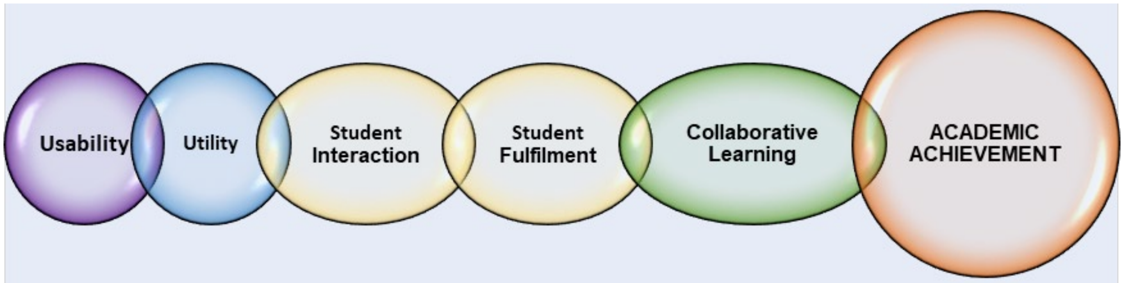

Figure 1-7 Potential for academic achievement with AI as peer-to-peer support

Figure 1-7 illustrates areas essential to academic achievement in the context of this study depicted by various works (Bitkina et al., 2020; Stanton & Jensen, 2021; Baidoo-Anu & Owusu Ansah, 2023; tom Dieck et al., 2023; Ouyang, Wu, Zheng, et al., 2023; Gardašević et al., 2023). Relevant topics include:

- Usability describes how easily students can use the AI-assisted platform (Bitkina et al., 2020).
- Utility denotes how effectively students think an AI-assisted platform meets their needs (Stanton & Jensen, 2021).
- Student interaction encapsulates diverse ways students communicate and engage with an AI-assisted platform and peers (Baidoo-Anu & Owusu Ansah, 2023).
- Student fulfilment: represents students' satisfaction with their academic experiences concerning AI-assisted platforms (tom Dieck et al., 2023).
- Collaborative learning involves students working together to achieve common academic goals (Ouyang, Wu, Zhang, et al., 2023).
- Academic achievement: measures a student's success in their educational pursuits, such as grades and completion of assignments (Gardašević et al., 2023).

One must analyse the structure of assessments and assignments to evaluate AI-assisted academic systems targeting learning outcomes such as critical thinking and problem-solving in alignment with sought graduate attributes, among other factors (Austen et al., 2023 & El-Amin, 2023). According to research, AI-driven platforms that provide individualised training, like Smart Sparrow, can raise student retention rates (Zanker et al., 2019). However, does improved engagement with a platform influence student grades, performance, and retention rates?

Incorporating contemporary innovative technologies, like peer-based learning platforms, has the potential to enhance engagement as part of a student belief system through the development of effective strategies. The student belief system impacts engagement levels (Schunk, 1991). If students perceive themselves as capable learners, they are more likely to engage actively with the material. Conversely, negative self-perceptions can lead to disengagement and a lack of participation (Li et al., 2024). This strategy challenges learning and teaching (Davis, 2023)[3].

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3 A recent report evaluating the status of the transformation project in South African higher education revealed: "Although massification has meant that a significantly greater proportion of black South Africans are managing to access higher education, the aspirations of many students have not been met. High dropout rates, especially in many universities, continue to damage the livelihood prospects of many students and their families, especially those in follow-quintile schools. In contrast, a higher education qualification would have the largest public and private

In response, institutions are implementing policies to enrich undergraduate learning experiences across various learning and teaching stages (Baashar, 2022). The emergence of AI platforms as a facilitator of peer-to-peer support, which may enhance engagement, accompanies this transition in learning and teaching (Ardawi, 2022).

1.7 AI: The Facilitator of Peer-to-Peer Support

Integrating artificial intelligence (AI) has led to significant transformations across various sectors, including learning and teaching (Hasan & Hasan, 2023). AI-powered tools in learning and teaching have been instrumental in refining teaching methods (Hattie, 2023). Academic institutions must implement protective measures to create a supportive environment for students' knowledge acquisition, adjustment, and retention. There is a recognised need to expand on the retention models proposed to enhance the accuracy of existing conceptual models and develop a new theory (Kember et al., 2023). This expansion should consider the interconnectedness of external and internal teaching methods influencing voluntary student dropout.

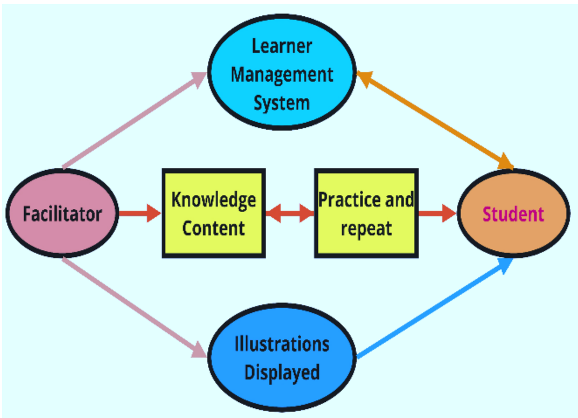

Figure 1-8 Traditional teaching method (Tularam, 2018)

Figure 1-8, traditional teaching methods revolve around a teacher-centred approach, where students passively receive knowledge (Gurudeo, 2018). Though this model has seen past successes, critics argue that it may not equip students with essential skills, long-term

returns regarding individual, family, and social transformation, especially for these students. In this context, there are many transformation challenges associated with teaching and learning which directly impact the potential of higher education to contribute to the restructuring and transformation of South African society at large" (Luescher, 2023, p. xvii).

knowledge retention, or business thinking skills (Alshehhi et al., 2023). They say that students may need help to keep information beyond the end of the semester, suggesting a potential limitation of the lecture-based model (Yufereva & Derkach, 2023). Therefore, there is a need to explore innovative, student-centric pedagogical strategies that can enhance learning outcomes (Tularam, 2018; Ren, 2023).

Enabling facilitators to explore and experiment with diverse teaching methods is essential for perfecting student-centric approaches (Dutta, 2022; Tularam, 2018). Pandey (2023) suggests that this process necessitates continuous monitoring of student progress and adjusting teaching and learning techniques as required. Advocates of this approach emphasise that students have the potential to surpass their current achievement levels, highlighting the importance of raising academic expectations and enriching learning experiences (Aulakh et al., 2023). Universities can enhance learning outcomes and help students achieve their full potential by promoting innovation tailored to their needs, supported by the flipped classroom approach (Mukhitdinova, 2023).

Flipped classrooms have gained popularity as an alternative teaching and learning approach across different learning and teaching settings Huang et al. (2023) & Brewer & Movahedazarhouligh (2019), as shown in Figure 1-9. “The flipped classroom approach aims to improve learning outcomes by promoting learning motivation and engagement. Recommendation systems can improve learning outcomes as well. Huang et al. (2023: Abstract) note that the rapid development of artificial intelligence (AI) technology has created “various systems to facilitate student learning”.

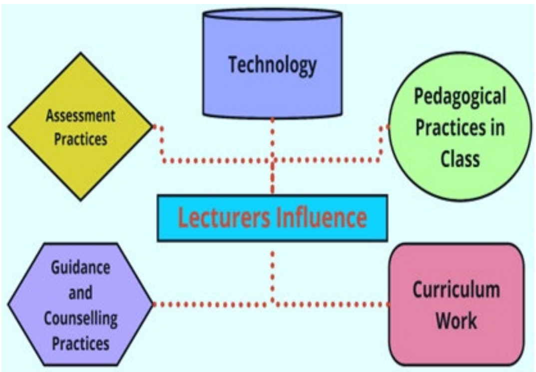

Figure 1-9 Central dimensions of the flipped training module (Sointu et al., 2023)

However, a growing need exists to understand the factors contributing to student satisfaction in a flipped learning environment (Martin & Bolliger, 2018; Algarni, 2023).

The flipped classroom model restructures the sequence of learning activities and positions students responsible for studying materials, such as hybrid lectures and texts (Larson & Linnell, 2023; Houghton, 2023). Students prepare for learning with study materials before classroom sessions, focusing on higher-order thinking activities like peer instruction and problem-solving (Abeysekera & Dawson, 2015; Strelan et al., 2020). Technology integration and an emphasis on active learning provide students with increased autonomy and flexibility, potentially leading to more effective learning outcomes (Alexander et al., 2019).

Brewer & Movahedazarhouligh (2019) state that the flipped classroom model, shown in Figure 1-9, requires students to take the initiative in their learning, necessitating extensive preparation and review of pre-class materials. Schunk (2023) suggests that shifting from passive to active learning could improve students' self-regulation. However, for effective use of this model, Sointu et al. (2023) note that students must be well-informed and supported in learning the understanding and skills required. AI understands these characteristics as part of facilitating peer-to-peer support. Educational AI Tools (EAITs) emerged as machine learning technology advanced to support teachers in making informed choices about their instruction (McGraw Hill Education, 2011). However, reliable information on instructors' attitudes towards resources is still insufficient, and there is currently limited integration of these technologies in educational contexts (Choi et al., 2022).

Further study is required to develop an enhanced framework for a human cognitive structure to determine the human aspects that impact instructors' acceptance of Educational Artificial Intelligence Technologies. The theory presents a conceptual framework for comprehending a range of factors, including part of a student belief system, learning achievement, and pedagogical effectiveness, connected to using AI peer platforms as a method of instruction (Choi et al., 2022; Schommer-Aikins, 2012). The frameworks outline the objectives of AI in facilitating peer-to-peer support.

1.8 Introducing the Underpinnings of the Study

The study aims to understand the role of AI in peer-to-peer learning relationships, which involves the identification of specific technology and people relations. By exploring these aspects, the study aims to clarify how AI may impact the learning-teaching process, particularly in enhancing student learning outcomes and improving the learning process.

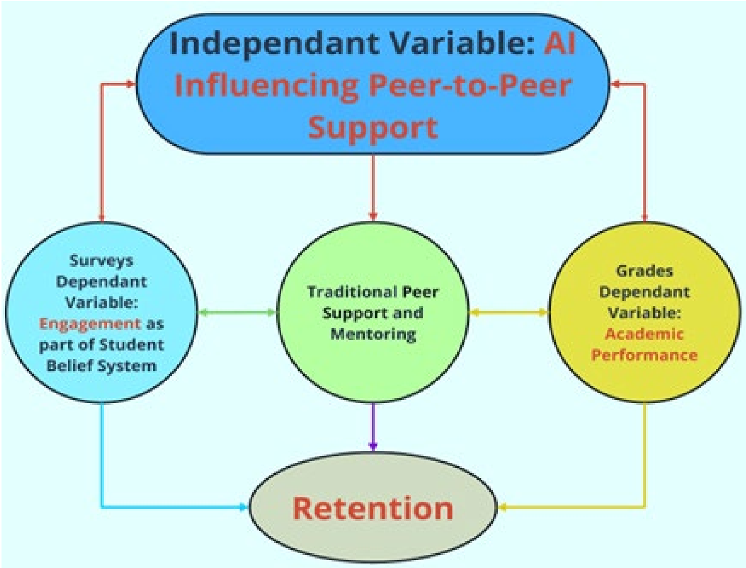

Figure 1-10 AI's Influence on Engagement and Academic Performance

Figure 1-10 illustrates the interconnectedness of AI-facilitated peer-to-peer support, engagement as part of a student belief system, traditional peer support, and grades as academic performance in influencing retention and willingness to return. This figure also addresses the gap in the literature highlighted in Chapter 2. The diagram demonstrates how these components interact to enhance understanding and support strategies to improve student retention rates.

Figures 1-10 identify the independent variable (AI-Facilitating Peer-to-Peer platform) and the dependent variables (Student Engagement as part of the Student Belief System and Academic Performance). Engagement and academic performance are perceived to influence student retention, an outcome. The positioning of AI as an independent variable suggests exploring how AI interventions could enhance traditional peer-to-peer support mechanisms to improve engagement, performance, and retention rates. It will ascertain if engagement affects performance. Works rely on contemporary studies, strengthening relevance to current educational challenges and solutions (Pascarella & Terenzini, 1979; Bean, 1988; Tight, 2019; Rowe et al., 2022; Tinto, 1975; Santos et al., 2023; Guarda et al., 2023). There is an alignment with existing theories on peer learning and retention, though it uniquely combines these with AI. Situating AI within the peer learning context suggests a novel inquiry area that integrates technology with traditional educational practices. Figures 1-10 support a mixed-methods approach by distinguishing between different types of variables and outcomes. This approach allows quantitative measurement of variables like academic performance and qualitative analysis of how AI influences engagement and peer interactions.

Figures 1-10 effectively set the stage for investigating how AI-enhanced peer-to-peer learning can impact student retention through engagement and academic achievement changes. It provides a research roadmap while integrating the background with new and established seminal contributions.

The study focuses on the complexity of adopting AI for facilitating peer-to-peer learning; it discusses the existing literature and data and analyses the utility and limitations of AI in this learning environment. Via sensitivity to students' voices, the study's findings hope to contribute to attaining a comprehensive vision of how AI affects education.

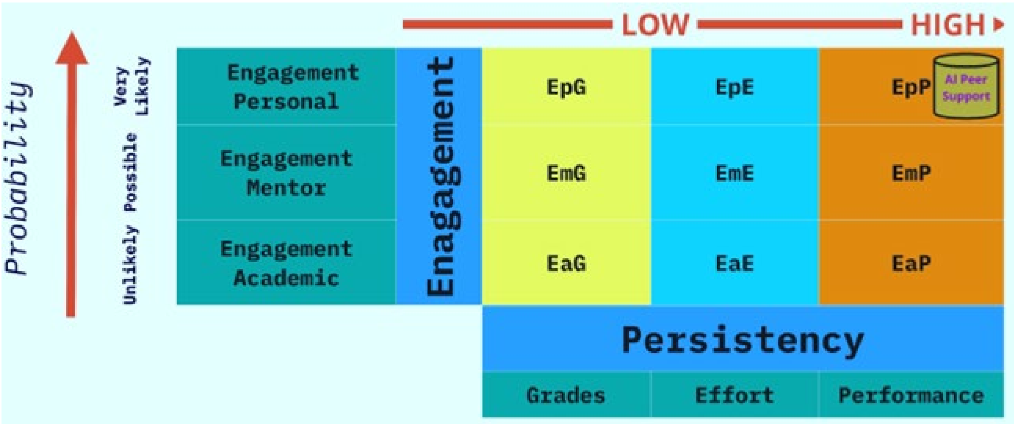

Figure 1-11 The adapted matrix by Kimmons, Graham and West (2020, p.189) categorises Engagement and Persistency.

Figure 1-11 positions the AI platform as a peer-to-peer support facilitator according to its expected impact, supporting the study's aims. This link identifies engagement types with persistence outcomes, especially AI peer-to-peer support.

AI peer-to-peer support potentially impacts engagement, its different types, and persistency, including grades, pass rates and performance. It is pretty likely that with the help of AI peer-to-peer support, medium pressure affects the level of effort and activity in personal, mentoring, and academic domains (EpE, EmE, EaE). AI peer-to-peer support anticipates improving the positive relationship between student persistence for factors like grades, work effort, etc, with other aspects of their lives and engagement levels in the personal, mentor, and academic roles defined for students (EpP, EmP, EaP).

AI peer-to-peer support may affect courses and learning activities that correlate to student engagement and course persistence due to the probable changes in grades, pass rates, and performance. AI mentoring and AI peer-to-peer support are less likely to alter students' grades via personal, peer-to-peer support, and academic interactions only (EpG, EmG, EaG, i.e. Low Probability).

Understanding the form of engagement is central to helping determine the effectiveness of AI peer-to-peer support in improving students' performance. It is also possible to distinguish between personal contact, contact with a mentor, and academic contact, all of which influence a student's learning process and success differently. This division helps analyse the level and extent of use of AI in various areas regarding students' engagement and engagement level.

- Engagement Personal (Ep): Interaction is a focused but familiar way of interaction – that of a personal nature.
- Engagement Mentor (Em): The interaction involves tutorage, which is the provision of advice or information by an expert.
- Engagement Academic (Ea): The interaction is related to academic content and topics and involves participation in activities.

The y-axis categorises the probability of engagements, starting from unlikely to very likely. The x-axis represents low to high engagement with AI peer-to-peer support. The degree of engagement rises as one rises from the bottom end of the y-axis to the top and progresses from left to right on the x-axis.

Persistency outcomes include:

- Grades (G): Students' academic performance based on their recent grades.
- Effort (E): Measuring the effort the students are willing to make in their studies.
- Performance (P): Assessing overall class performance, including effort, participation, and grades achieved. The extent of AI peer support impacts student attendance, performance, grades, achievement, and pass rates.

Figure 1-11 illustrates several anticipated expectations. Various types of engagement may be boosted through the help of AI peer-to-peer support, thereby impacting persistency indicators such as grade, effort, and performance. What makes this level of AI peer-to-peer support most effective in increasing high levels of overall personal, peer, and academic performance is the presence of high levels of personal engagement. Therefore, they imply that incorporating AI within educational facilities may enhance student involvement and academic performance through high personal, peer, and scholarly engagement.

This research looks into participation and performance to ascertain how they affect the students' choice to extend their education. These factors will assist in comparing an AI peer-to-peer support platform to traditional peer-support techniques. Also, the research will evaluate the students' perception towards AI peer-to-peer support to determine its effectiveness in enhancing students' performance. Central to this investigation is the pivotal question: To what extent are more positive outcomes reached by the students when accessing AI peer-to-peer platforms?

A thorough design and methodology strategy is needed to undertake this case study on the influence of AI on peer-to-peer support, engagement and grades and pass rates.

1.9 Introducing Design and Methodology

Figure 1-12 outlines this study's research design and methodology by introducing the method applicable to this study. The following section outlines these components:

Philosophy	Approach	Methodological Choice	Strategy	Time Horison	Techniques and Procedures
Interpretivism with a Positivism Approach	Induction	Mixed Methods Qualitative Quantitative	Case Study	Longitudinal	Analysis of External Data

Figure 1-12 Design and Methodology

The Research Onion informs the research design of the study (Saunders *et al.* 2019) and includes the following considerations:

- Philosophy: The study employs a philosophy of interpretivism with a positivist approach. Interpretivism prioritises comprehending students' perspectives and experiences with the positivist approach, stressing practical solutions and results.
- Approach: Instead of evaluating hypotheses, this study takes an inductive approach, whereby theories are developed based on observations and discoveries.
- Methodological Choice: A mixed methods approach is used in this research, combining quantitative and qualitative techniques. Combining the breadth of quantitative data with the depth of qualitative data enables this method to provide a thorough analysis.
- Strategy: The case study method describes a specific event or situation that could take

place in the framework of the investigated subject area. Therefore, this strategy implies a comprehensive case-specific result.

- Time Horizon-Longitudinal Designs that use continuous or repeated measurements to cover fixed events or interventions over time—typically in years or even decades. Commonly, they are descriptive, and only quantitative and/or qualitative data on outcomes is available without any intervention from outside. An evaluation occurred after students experienced relevant interventions over a period. The data on the consequences of this intervention within a cohort were then collected and analysed retrospectively.
- Techniques and Procedures: A consequence of this research entails analysing external data to arrive at conclusions.

The study's research method relies mainly on an interpretivist and “inductive thematic saturation approach where themes are identified within the data and the extent to which insights are gained from this process” (Saunders et al. 2018: 1898). The method used is a mixed-method basic convergent approach (Creswell, 2014). Quantitative and qualitative data are gathered simultaneously, analysed distinctly, and then integrated during interpretation (Creswell, 2014). I have used archival surveys for the theme interpretation and final grades and pass rates for the statistical analysis from the 2017 to 2023 academic years.

Eisner (2017, p.33) described a qualitative study as “nonmanipulative, that is, it tends to study situations and objects intact, and it is naturalistic”. This study uses the existing archival surveys as its data instruments, maintaining its natural form. He also emphasised that an investigation must relate “to the self as an instrument” (Eisner, 2017: 33), where “the self is the instrument that engages and makes sense of the situation. This is often done without an observation schedule” (Eisner, 2017: 34).

The surveys were administered through the Internet using a Learner Management System. It was an organised collection; the participants would submit the responses on a given date and time. The grade and pass data was then copied into Excel to ensure no access by any unauthorised personnel (Girvan, 2012). The researcher accessed the University’s database to retrieve the aggregated number of students, grades, and pass rates.

The technical, design, and methodology optimise the paradigm for a balanced, comprehensive research model that integrates theory and implementation (Saunders & Lewis, 2017). One can state that the analysis of this study supports the chosen strategy, relying on theoretical contributions.

1.10 Study Outline

Chapter 1 of this study establishes a general background of how AI could help foster peer learning, evaluate its outcome, and analyse its benefits to engagement and accomplishments. Before offering the empirical findings of this research, the chapter provides a literature review that explores the previous works and theoretical papers on AI, teaching, and learning. Chapter 3 focuses on the research design and methodology used in developing this study and uses both qualitative and quantitative methods to investigate the extent to which the use of AI affects peer-to-peer and learners' learning engagement. It has the sampling method, data gathering, and issues related to ethical conduct. Chapter 4 concludes the study by providing a platform to present and analyse the findings needed to advance the understanding of whether or not AI can help increase knowledge exchange and what may result from its use in peer-to-peer learning. Chapter 5 provides a research analysis that compares the existing literature and recommendations for future works. It acknowledges that AI is an advancing field, and the continuous enhancement of this field is crucial, especially given its present and future importance.

CHAPTER 2 LITERATURE REVIEW

Grounded in the theories and findings of Tinto (1975); Bean (1980); Bork (2002); Tight (2019); Ouyang, Wu, Zheng, et al. (2023), this longitudinal case study explores AI's influence as peer-to-peer learning on student engagement, academic grades, pass rates and influencing retention. This literature review focuses on AI peer-to-peer support and its influence on engagement and academic performance through user-centric AI platforms (Lee, 2014). The study asserts that AI, as a peer-to-peer facilitator, can augment lecturers' learning and teaching strategies, enhancing adaptability and performance (Williams & Reddy, 2016).

This study evaluates student performance through final grade performance, comparing pre- and post-AI performance levels (Lynch & Hennessy, 2017). It also analyses historical empirical surveys regarding student engagement as part of a student's belief system linking social network analysis (SNA) by combining qualitative and quantitative network approaches (Froehlich et al., 2020). Proponents view this approach, Mixed Methods Social Network Analysis (MMSNA), as a "remedy" against the criticism of heavy reliance on quantifying qualitative data. (Froehlich et al., 2020). This study acknowledges the challenges in personalised learning highlighted by (Bloom, 1984; Sottilare, 2018). While recognising AI's benefits, like improved efficiency and adaptability, the need for further research is stressed. It will explore AI's capabilities and limitations in addressing personalised learning nuances (Chan & Hu, 2023).

The bibliometric literature, guided by the work of Donthu et al. (2021), analysed keywords from studies on learning and teaching, beginning with a review that explores the gaps in AI's impact on learning and teaching.

2.1 Gaps

A bibliometric literature review investigates AI's role in peer-to-peer learning. The researcher chose A bibliometric review to uncover emerging trends in article and journal performance, collaboration patterns, and research constituents, and to explore the intellectual structure of a specific domain in the extant literature" (Donthu et al., 2021pt.Abstract). "And its popularity can be attributed to (1) the advancement, availability, and accessibility of bibliometric software such as Gephi, Leximancer, VOSviewer, and scientific databases such as Scopus and Web of Science" (Donthu et al., 2021: Abstract). It focuses on its impact on engagement and academic performance, exploring these through various research questions.

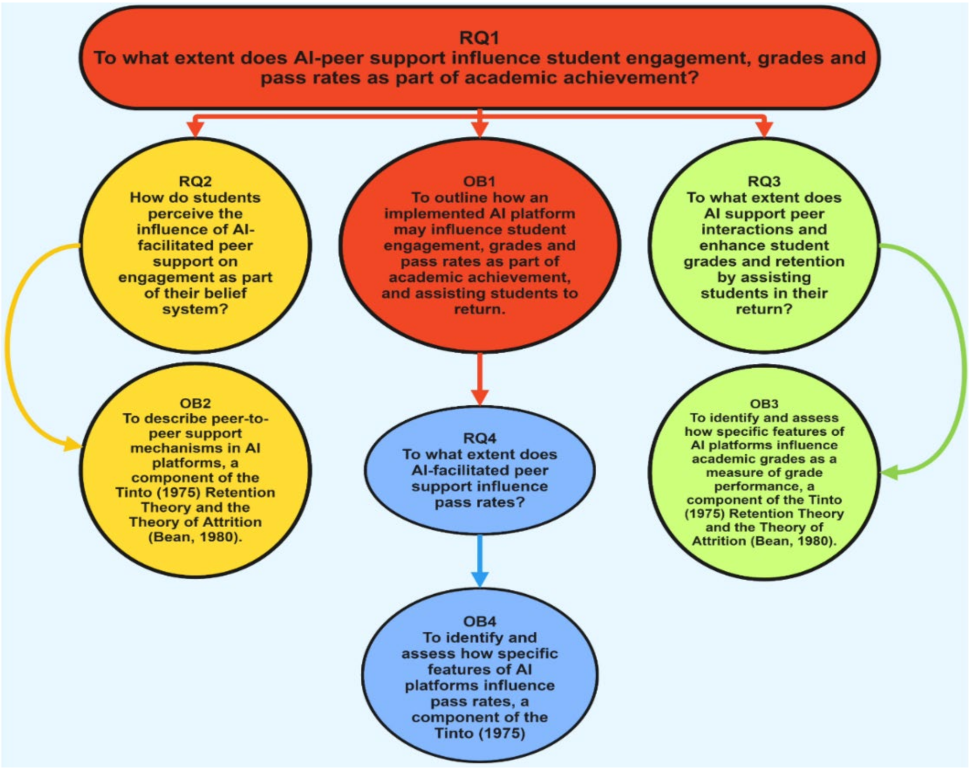

Figure 2-1 Research Question and Objective Alignment

The questions investigate how peer support, facilitated by AI in learning platforms, influences student engagement, grades and pass rates as part of academic performance. It seeks to identify specific features of AI peer-to-peer support that contribute to these outcomes. Figure 2-1 categorises these inquiries into sub-questions, correlating them with learning and teaching theories. These theories encompass retention Tinto (1975); Bean, (1981) and engagement belief theories (Garmendia et al., 2023). This alignment aids in framing the research questions within established theoretical contexts.

Previous research has explored AI separately in learning and teaching, and the effect of traditional peer-to-peer techniques in learning is understood (Topping & Ehly, 1998; Oni & Viswanathan, 2016; Sharma et al., 2023). However, there is a possible gap in understanding how AI facilitates peer-to-peer learning and influences engagement and performance (Alessandro et al., 2021). This paper on AI intervention studies how students interact, perform, and pass in peer-supported environments by reviewing the literature gap.

In Donthu et al.. (2021, para.289), “a co-word analysis can be used as a supplement to enrich understanding about the thematic clusters derived from co-citation analysis or bibliographic coupling because the themes formed through the commonalities in publications tend to be relatively general (Chang, Huang, & Lin, 2015), and thus, the use of co-word analysis can help researchers to elaborate on the content of each thematic cluster. Second, "a co-word analysis can be used to forecast future research in the field, which can happen when "notable "words" from the publication's implications and future research directions are used in the analysis" (Donthu et al., 2021: 289).

A co-word analysis is used in this bibliometric review to address the research questions and objectives. The study progresses through interconnected sections, such as peer-to-peer support, student engagement, grades, pass rates, and retention. Each section highlights a different aspect of AI in learning and teaching. The co-words are then thematically categorised and displayed in VosVeiwer®.

A co-word analysis, through a hermeneutic approach of 1113 research publications on AI and learning, reveals noteworthy developments (Boell & Cecez-Kecmanovic, 2014). These include the overall impact of AI on pedagogy (Kolchenko, 2018; Taneri, 2020; Gupta, 2022; Mota, 2023; Minn, 2022; Chan, 2023; Toksha et al., 2022; Bozkurt & Sharma, 2023; Woithe & Filipec, 2023; Capuano & Caballé, 2020). Magnisalis, Demetriadis and Karakostas (2011) contribute to the literature on the growth and impact of intelligent, adaptive systems for aiding collaborative learning (AICLS).

The search for AI in peer-to-peer learning found less specific content, suggesting an underexplored area. The discourse primarily focuses on AI's role and functions within general pedagogy and the teaching-learning relationship, as illustrated in Figure 2-2.

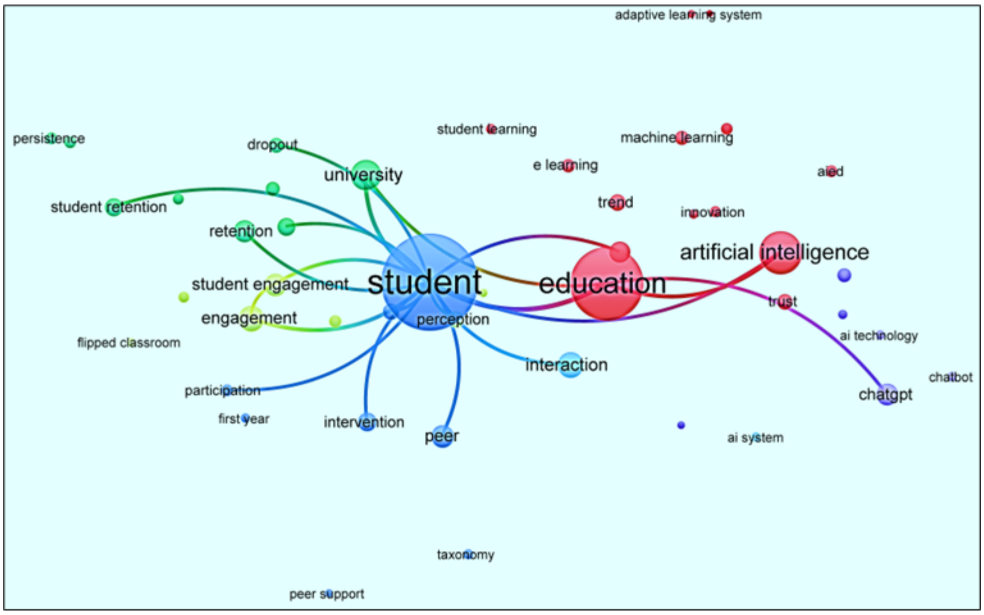

Figure 2-2 Keywords and Terms 2020-2023

“To facilitate the broad adoption of this technology, research is required to understand the factors contributing to user acceptance of AI" (Kelly et al., 2023).

Earlier focus and current research on AI as peer facilitators are in the medical sector, where Rowe et al. (2022) stated: “that the introduction of AI-based systems within the health sector is likely to have a significant influence on physiotherapy practice, leading to the automation of tasks that we might consider core to the discipline”. During 2023, a significant focus on ChatGPT was clear, with 16 keyword and term occurrences and a correlation coefficient of 20. This concentration is particularly noticeable in works published in 2022 and 2023. Terms like "satisfaction" and phrases such as "learn innovatively" and " engagement" are indirectly associated with ChatGPT.

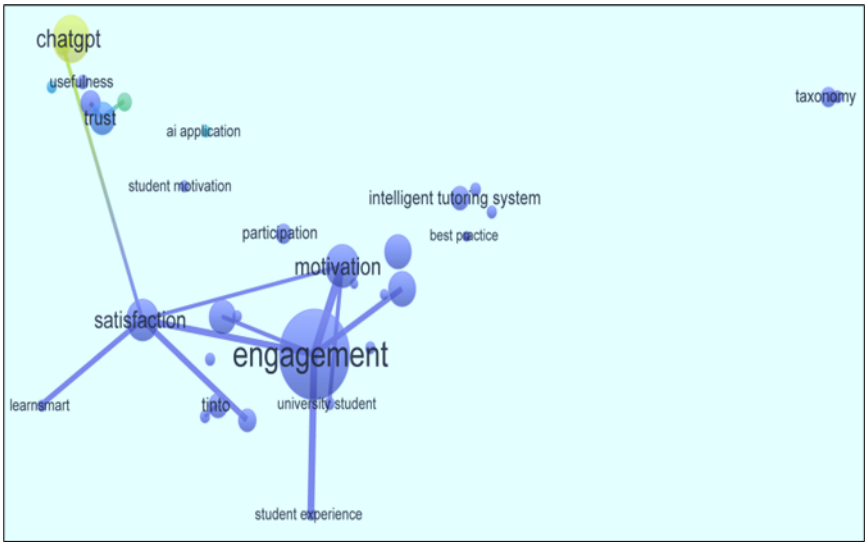

Figure 2-3 Links to ChatGPT 2020-2023

Notably, there needs to be more association with AI applications, taxonomy, student motivation, participation, and peer or peer-to-peer support. Refer to Figure 2-3 for a visual representation of the links to ChatGPT. However, the absence of alignment between student motivation (Tinto, 2017) taxonomy, intelligent tutoring system, participation, and best practice reveals a substantial research gap, as shown in Figure 2-4. Unexpectedly, the relationship involving ChatGPT lacks references to peer-to-peer support. Figure 2-4 outlines the research opportunities when exploring AI. Integrating AI into peer tutoring raises intricate questions about its influence on students' beliefs about Engagement, academic achievement, and learning platforms affecting retention.

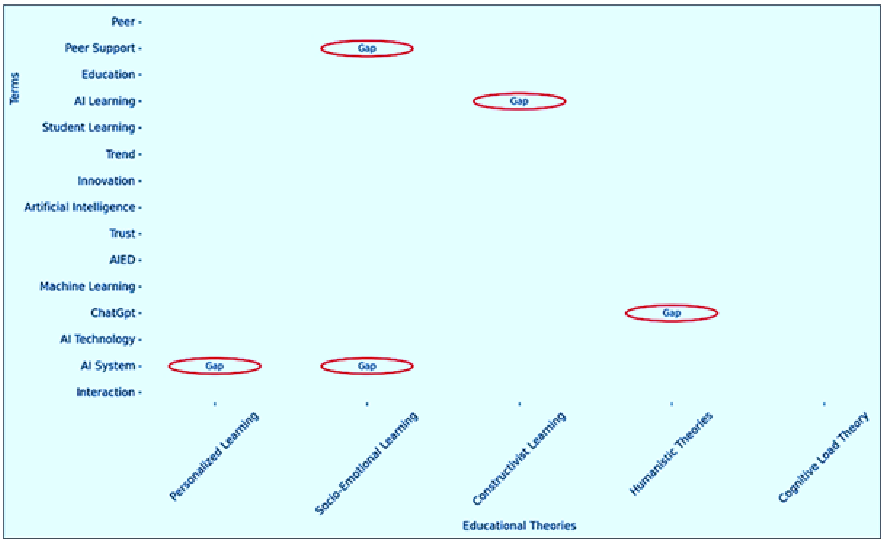

Figure 2-4 Gap matrix aligned to theories

The mentioned theories—from Personalised Learning to Cognitive Load Theories—offer seminal perspectives to evaluate AI's potential and limitations and present a proposed conceptual framework and fundamental concepts.

2.2 Key Concepts

Key concepts provide a comprehensive foundation for the literature review, each playing a distinct yet interconnected role in shaping the investigation into the impact of AI-assisted platforms in learning and teaching. Table 2-1 presents vital concepts and purposes related to the research questions that support this study.

Table 2-1 Key Concepts

Concepts	Definition	Purpose
Academic Achievement	Grade point average (Liu & Liu, 2000).	I am measuring the influence the intervention has on student grades.
Adaptive Learning Technology	Learning and teaching technology adapts to individual student needs, tailoring content to their pace and understanding (Xiao et al., 2020).	AI platforms customise learning to improve Engagement and achievement.
Artificial Intelligence (AI) in Learning and Teaching	AI technologies, such as machine learning algorithms and adaptive learning software, are applied in learning and teaching for personalised tutoring (Shemshack & Spector, 2020).	The focus is AI's role in peer-supported learning and teaching, examining its effects on achievement and Engagement.

Concepts	Definition	Purpose
Engagement	It involves the level of interest, enthusiasm, concern, and hope students have when learning or being taught, including the desire to learn and elevate their education level. In general terms, students learn better when they are curious, interested or motivated as opposed to when students are bored, indifferent, demotivated or in some other way disinterested; higher levels of student engagement or increased levels of student engagement are typical goals set by educators (Glossary and Great Schools Partnership, 2016). In many different contexts, however, student engagement may also mean how university leaders, lecturers or any other adults can ‘engage’ a learner more formally in the process of decision-making in university, in the process of shaping programs and learning activities (Glossary and Great Schools Partnership, 2016) and (Alrashidi et al., 2016).	Its relevance to the study facilitates different engagement dimensions, including intellectual, emotional, behavioural, physical, social, and cultural. As a result, the study can examine how the factors affect students' engagement levels and how AI tools may help with the peer-to-peer learning process. Interacting with the students in these ways can improve their retention and performance, which is essential for creating reliable AI-based teaching solutions. Understanding these engagement types can help conceptualise how AI can enhance learning and be more inclusive and engaging.
Peer-Support Technology	Tools for peer learning include online forums, social networks, tutoring platforms, and collaborative software (Topping, 2005).	Explore AI platforms' effectiveness in offering peer-to-peer support, focusing on students' engagement beliefs.
Personalised Learning (PL)	Individualising learning tailors content and instruction methods (Kem, 2022).	Understanding the impact of AI platforms' customisation on academic success and student engagement is crucial.
Peer-to-Peer support	The process involves individuals with shared experiences helping each other as equals (Zhao et al., 2021).	Peer-to-peer support in AI platforms and their impact on student engagement perceptions and performance.
Retention	Tinto (1975)-Positive faculty and student relationships also position students to adjust to academic and social structures, improving students’ achievements and graduation rates (Hagedorn, 2005).	The more basic is centred on academics and AI platforms to help students fit within and engage with.

Concepts	Definition	Purpose
A Belief System umbrella comprises two significant components: Engagement and Support Systems.	Increased physical and mental activity among students concerning their academic work and group study enhances a deeper meaning of learning and commitment to education (Schommer-Aikins, 2012).	Researching the effects of artificial intelligence-related platforms on the overall perceptions of student engagement and the efficacy of peer assistance becomes necessary.

The narrative outlines several fundamental concepts and their purposes, providing a comprehensive understanding of the elements involved in the study. Considerations include the following:

- The academic grade point average reflects the university's student outcomes or accomplishments (Liu & Liu, 2000).
- Adaptive Learning Technology, defined in this context, is the ability of any designated tool used in learning and education to change with time as the learners use it. These technologies adapt the content delivery in line with a specific student's rate and competence or knowledge level, thereby observing the student's education needs and facilitating learning in a way that allows for the students' enhanced understanding and mastery of the subject matter (Xiao et al., 2020).
- Artificial Intelligence (AI) can revolutionise operations by engaging students through the intervention of Artificial Intelligence (AI). Personalised learning facilitates learning and teaching content to meet learners' needs regarding competency and speed (Shemshack & Spector, 2020). Moreover, an AI system can interpret data from the external environment, learn from the information obtained, and effectively attempt to achieve certain goals and perform specific tasks while applying flexibility. This flexibility allows every learner to have their learning process addressed dynamically for improved education achievements (Kaplan & Haenlein, 2019).
- Artificial Intelligence (AI) in learning and teaching incorporates intelligent technologies in the learning environment. This integration involves using artificial intelligence, learning algorithms, programs featuring self-learning and institutional learning, and automated administrative processes to offer students and instructors a unique learning and tutoring experience (Luckin *et al.*, 2016). Advanced technologies customise the content to fit a student's individual needs, automating most processes that may be time-consuming while increasing the efficiency and effectiveness of the whole teaching and learning process.

- Engagement may encompass intellectual, emotional, behavioural, physical, and cultural dimensions(Glossary and Great Schools Partnership, 2016). Engagement is a complex term that emphasises students' various patterns in motivation, cognition, and behaviour (Alrashidi et al., 2016). "Engagement is broadly a positive and proactive term that captures students' quality of participation, investment, commitment, and identification with university and university-related activities to enhance students' performance" (Alrashidi et al., 2016:42).
- Peer-support technology includes tools that help students learn with and from each other by providing peer-to-peer learning support and improving collaborative learning experiences. In other words, when they affect their learning and relate with other learners, they compel the group members to embrace various coexisting strategies and support all learners in realising their academic endeavours. The technology can also be used differently, for example, on the forums, Facebook, Yahoo, and Messenger, peer tutoring, and interaction software that promotes learning (Topping, 2005).
- Traditional peer support is a process that involves individuals with shared experiences or shared challenges coming together as equals to supply and receive help based on the knowledge gained through shared experiences (Zhao et al., 2021).
- Personalised Learning (PL) individualises the learning flow to personalise (individualisation) content and tailor tuitional methods (differentiation) (Spector, 2016).
- Peer-assisted learning (PAL) is a learning and teaching approach that harnesses the power of peer interactions to supplement student learning, Engagement, and success (Topping & Ehly, 1998).
- Personalisation and individualised learning may be explained as "learning that involves individual students customising the learning program with a particular pace (individualisation), tailor-made instructional method (differentiation), and contents for personalised learning" (Kem, 2022: 386–390).
- Retention in terms of the Frameworks, as per Tinto (1975), suggests that successful integration into the academic and social system, individual commitment to graduation, and the institution yield changed outcomes. A student who enrols in university and stays enrolled until qualification completion is a "persister" (Hagedorn, 2005: 90–101).
- From the perspective of Tinto (1975) and in terms of the framework, student engagement is the active involvement of students in academic and social activities within a university. Later theories expanded on engagement, emphasising active and collaborative learning, interactions with faculty, and a supportive campus environment as fundamental to student engagement (Pascarella & Terenzini, 1979; Kuh et al.,

2008).

- The student belief system constitutes a broader belief system of students, not individual beliefs. Contextually, it refers to students' overall perceptions and attitudes towards this platform, including ideas about their utility, effectiveness, and role in their learning experience. Effectively, it is a set of views of what is right and wrong and what is true and false (Schommer-Aikins, 2012).

In supporting Table 2-1, the principle of personalisation or individualisation may be regarded as one of the main features of an AI system because this characteristic reflects the essence of the vital principle that determines the AI setting of the contemporary period (Kember & Hicks, 2023). The area of interest is the use of AI in learning and teaching, as well as related terms like learning technology, peer-supportive technology and knowledge. The table points to the need to look at the nature of technology regarding peer interaction for improved learning and teaching with help from AI as a beacon for improving learners' engagement and results, amongst other factors (Jia et al., 2023). It outlines risks like the algorithmic bias that would affect the fairness of applying the peer-based learning platform. It also stresses supporting the students' conceptual frameworks, a vital precondition to integrating those new technologies into education and training processes. Sensitisation of such issues is crucial in making education accessible and congenial to all students (Areepattamannil et al., 2023). Therefore, these areas should be established as mandatory benchmarks for success and achievement in AI to achieve its proper regulation and ethical utilisation.

The study aims to synthesise the fundamental concepts through the seminal frameworks into themes: artificial intelligence, peer-to-peer support as part of AI, engagement as part of a student belief system and AI, grades and pass rates as part of AI which concerns the retention of students and their willingness to return to university.

2.3 Conceptual Framework and Engagement Matrix

The study uses an adapted matrix, Figure 1-11, presented in Chapter One, section 1.8, and seminal literature to categorise data according to the foundational areas of interest: Engagement and Academic Achievement, influenced by peer-to-machine support (Kimmons et al., 2020). The matrix supported by Figure 2-5 helps identify the independent and dependent variables and align these with the relevant theories.

Chapter One's research question identifies the AI platform as an independent variable influencing the dependent variables—Engagement and Performance. The study aims to determine whether an engaging AI peer-to-peer support platform correlates with improved academic performance (Xu & Ouyang, 2022).

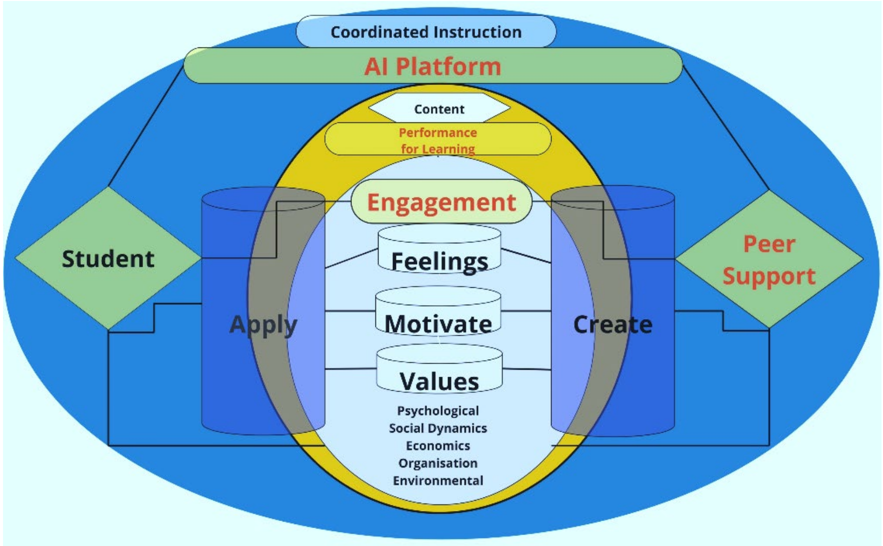

Figure 2-5 Conceptual Framework

Figure 2-5 implies a hierarchical relationship among the seminal framework constructs (Balilah et al., 2020; Halverson & Graham, 2019; Minsky, 1974). Figure 2-5 represents an AI platform integrated with a learning model comprising various components such as peer-to-peer support, student engagement, grades and pass rates. Each component contributes to the study's feasibility and methodology.

- AI Platform: This core technology facilitates communication and content transmission, collecting information on the learners, their interactions, and the results they achieve to enhance the learning processes. The study measures the AI's capacity to refactor content following the learners' reactions and their outcomes.
- Peer-to-Peer Support: Students assist each other with assignments and morale, enhancing learning and motivation.
- Engagement: Engagement includes students' involvement in the learning process, measured by metrics such as session times, interaction rates, and qualitative feedback.
- Performance: This involves evaluating learning activities to assess the effectiveness of AI-facilitated peer-to-peer learning, using proficiency assessments and score comparisons before and after AI implementation.
- Apply and Create: These processes involve students applying their learning and generating new content or solutions, which are assessed through project performance

and the quality of creative works.

All the sections in Figure 2-5 appear to be interrelated, and improved engagement and performance could be underpinned by, for instance, upgraded peer-to-peer support realised by AI. Determining the credibility and practicality of the study entails considering how these aspects co-relate and add up to learning outcomes' effectiveness through theoretical and numerical methodologies. Investigating these interactions will imply the effects of AI-overlaid peer-to-peer support on students' performance, interest, and educational efficiency.

The conceptual framework references Tinto's Model on the Integration of Students and Bean's Student Dropout Model Section (Tinto, 1975; Bean, 1980). The conceptual framework and matrix models maintain the relationship between social and academic connectivity and students' performance and enrolment. According to Tinto's (1975) retention theory, personal and educational activities that occur through the university influence students' persistence. Bean concentrates on how self-perception influences the intention and behaviour towards continuing the studies or dropping out. These models highlight that many complex processes affect students' achievements.

- Psychological: Questions which concern the readiness of students for classes, the usefulness of assignments in the learning process, and the directing function of SmartBook® are related to this area as the discussions of compelling studying motivation and cognitive approaches beware (Tajibayeva et al., 2023). These aspects are essential for knowing the elements that prevent or enhance learning through psychological predictors and AI-supportive educational tools.
- Social: Concerning the ease of use of Connect® and recommendations to other universities, the following questions come under this category. These inquiries concern everyday user engagement and the academic community's perception of how psychology and culture affect the use of AI in the students' context and the effectiveness of AI in the education system (Shinwari et al., 2023).
- Economic: The question regarding the enhancement of the worth by Connect® in the subject of Financial Management may include bias that is economic since it involves matters of costs, benefits, and use of resources (Yu et al., 2023).
- Organisational: Comments concerning the ways and the need to include Connect® into the curriculum and whether it should be a part of a lecturer's arsenal are procedural. They focus on the structural and delivery strategies of the learning content (Alfirević et al., 2023).

- Environmental: The suggestion of moving exams and tests online implicates ecological considerations, such as the digital learning environment and infrastructural needs (Abdigapbarova & Zhiyenbayeva, 2023).

The conceptual framework implies that a person must understand and develop the framework constructs that drive engagement to enhance performance. This alignment signifies that the platform should consider psychological, social, economic, organisational, and environmental aspects when designing interventions to improve student performance through engagement, aligning with the principles (Tinto, 1975; Bean, 1980).

In summary, the matrix and the conceptual framework collectively suggest a theoretical framework where "Framework Constructs" comprising Psychological, Social Dynamics, Economic, Organisation, and Environmental factors are foundational to "Engagement," which in turn is crucial for "Performance."

The influence of an AI platform on engagement and performance indicates that the study focuses on understanding how AI as a facilitator affects these two dimensions. This focus suggests that these constructs are nested within each other, forming a hierarchy where framework constructs are the bedrock supporting engagement, subsequently influencing grades and pass rates as part of the performance. The correlation between the matrix and the framework lies in the premise that an AI platform could be a significant tool within the framework constructs that enhance student engagement, leading to improved performance. The figures imply that bolstering engagement through AI could affect academic performance, aligning with Tinto's (1975) & Bean's (1980) theoretical frameworks, which underscore the importance of integration and student beliefs in educational success. Key concepts, artificial intelligence, peer-to-peer support and AI, engagement and AI, grades and pass rates and AI, and their relevance to the study to initiate this integration with the seminal frameworks are the basis for this study.

2.4 Seminal Frameworks

The use of AI peer-to-peer support for breaking barriers among AI, student engagement, pass rates, grades, and individual student development comprises multifaceted aspects, three of which are:

- Delivery: AI's delivery engagement mechanism significantly helps how students perform in their academic activities (Mandouit & Hattie, 2023).

- Tailoring Learning Tasks: Customising the tasks according to the lecturers' and operators' capacity within a student's specification based on cognitive levels (Kem, 2022).
- Features and Achievement: Feedback, in its real-time provision, plays a pivotal role in motivating performance (Tight, 2019).

Exploring existing literature and driving knowledge on these aspects relating to AI peer-to-peer support forms the baseline for reviewing the influence of AI on engagement, grades and pass rates and broad success of students.

2.4.1 Introduction

Higher education institutions currently face the challenge of attracting students who can adapt to varied academic demands (Alenezi, 2023). Effective policies are needed to enhance students' learning experiences across various levels (Algarni, 2023). These institutions must predict academic success early and tailor enrolment guidelines to prevent suboptimal achievement (Baashar, 2022). Research could expand to include predicting academic achievement for a broader student population using diverse predictive variables and AI models (Baashar, 2022).

The National Centre for Education reports that about one-third of first-year university students stop their studies before year two (NCES, 2020). Instructors must equip pupils with the cognitive and technological abilities necessary for future success as learning and teaching undergo considerable change due to the rise of artificial intelligence and automation (Hutson, 2022).

Recent developments in AI-powered platforms intend to improve student achievement, engagement, and retention (Bhimdiwala et al., 2022). These platforms use robot learning algorithms to dissect student data to deliver tailored learning experiences (Maurya et al., 2021). According to Ardaw (2022), the study showed that students were more engaged using Artificial Intelligence than academic methods. Depending on the students ' needs and interests, these platforms can use algorithms to tune learning content and delivery(Shilbayeh & Abonamah, 2021). It also helps define specifics so students can gain more proximal and distant engagement with the educational methodology and pedagogy (Shilbayeh & Abonamah, 2021).

The results of observing how students facilitate each other's learning can shed light on the interpersonal aspect of learning and teaching, even in environments where automation via AI is applied (Topping, 2005; Bauer et al., 2023). Earlier discussions link peer-to-peer support to student engagement, grades and pass rates as academic achievement (Arco-Tirado et al., 2020).

Recently, dropout rates of students from institutions have risen drastically (Hegde & Prageeth, 2018; Matschke et al., 2023). Higher education student dropout has been a perennial problem and a subject of scholarly interest for many years now (Fan et al., 2023). The first wave of research focused on the traits an individual could possess that could make them engage in such conduct. Nonetheless, the literature has broadened the coverage of the variables regarding a broader academic environment in recent studies (Lainjo, 2023). This shift shows that all the characteristics of the students and the external environment factors bear some responsibility for students' retention and success.

Moreover, the implications exerted on the establishments to identify and implement ways of reducing and combating student dropout remain a concern (Del Bonifro, 2020). A typical strategy that has emerged as a potentially feasible candidate is Data Mining (DM) (Guarda et al., 2023). DM collects student information to help decision-making for a specific purpose, like reducing dropout rates.

Retention in higher education is complex; 25% of students drop out after their first year (Midford et al., 2023). Research says intervention programs impact retention rates, especially during the first year, making it crucial to find students needing added early support (Lin, 2012). Tinto's "Model of Institutional Departure" underscores the importance of integrating students across structured academic and unstructured societal practices for success in higher education (Kerby, 2015). A supportive learning environment that promotes resilience, adjustment, and retention is thus vital (Kerby, 2015).

Finally, Peer-Assisted Learning (PAL) strategies enhance student-centred learning and promote cognitive development, perseverance, and motivation (Arco-Tirado et al., 2020; Rohrbeck et al., 2003) and can be further augmented by incorporating AI technologies. Using AI, PAL strategies may receive help from intelligent algorithms that analyse student data, preferences, and learning styles to create personalised recommendations for peer interactions.

Retention is vital in learning and teaching (Afzal et al., 2024). Such factors are of interest, such as the aspects of the platform that would help attract more students or support from the AI-cloud platforms to maintain relationships with learners and secure their continued involvement.

Seminal works form the baseline for reviewing the influence of AI on peer-to-peer support, engagement, grades and pass rates in the broader success of students.

2.4.2 Retention and Attrition

Retaining students is essential for individual students' accomplishment and necessary to measure the institution’s performance (de Cadiz & Barquin, 2023). Tinto's Model of Student Retention is among the most prominent approaches to explaining student retention factors, as illustrated in Figure 2-6 (Figueira, 2015). This model proposes that students' persistence in higher education depends on various connected academic and non-academic factors, such as embracing learning and teaching and communal integration, commitment, and background characteristics.

Parts of the Student Integration Model developed by Tinto (1975) and Bean’s (1980) Student Attrition Model share common themes used as a framework for the study. Both models recognise the diverse attributes, practices, and differences that students have at the time of their admission to the university, such as academic readiness, parental learning and teaching attainment, socioeconomic status, and learning aspirations (Chan & Hu, 2023). Once students enrol in a university, the models aim to illustrate how collaboration between the student and established surroundings shapes and transforms their attitudes, behaviour, and commitments (Prickett & Hayes, 2023).

Tinto’s Model of Student Retention postulates a constructive basis for understanding the varied aspects contributing to students' higher learning success (Tinto, 1975). Research shows that students will succeed when accountable to high achievement standards (de Cadiz & Barquin, 2023). Expectancies that are consistent and clear, particularly in academic advising, are foundational for students to understand the requirements for success in their courses and programs of study (Trivedi, 2022). Institutions should supply academic and social support, such as tutoring and mentoring, to enable students to continue their studies, especially those underprepared for university (Trivedi, 2022).

The study examines the influence of AI peer-to-peer support on engagement, grades and pass rates that form the Theory of Retention by Tinto (1975) and Attrition (Bean, 1988). it is noteworthy to understand certain constructs from these frameworks, including:

- Encouraging peer-to-peer support: Integrating artificial intelligence to augment peer-based interaction processes to boost learning achievements.
- Features Relevant to Grades and Pass Rates: From the frameworks, we will discuss how and what factors AI platforms use to recognise students at risk of failing and how the system adapts to support them.
- Functionalities enhancing engagement: Evaluating the tools, like predictive analytics, as to their impact on the engagement of the students.

For such purposes, it is necessary to study these areas to understand whether using AI-peer-to-peer support platforms can help increase the efficiency of student engagement, grades and pass rates and potentially reduce dropout rates (Tinto, 1975).

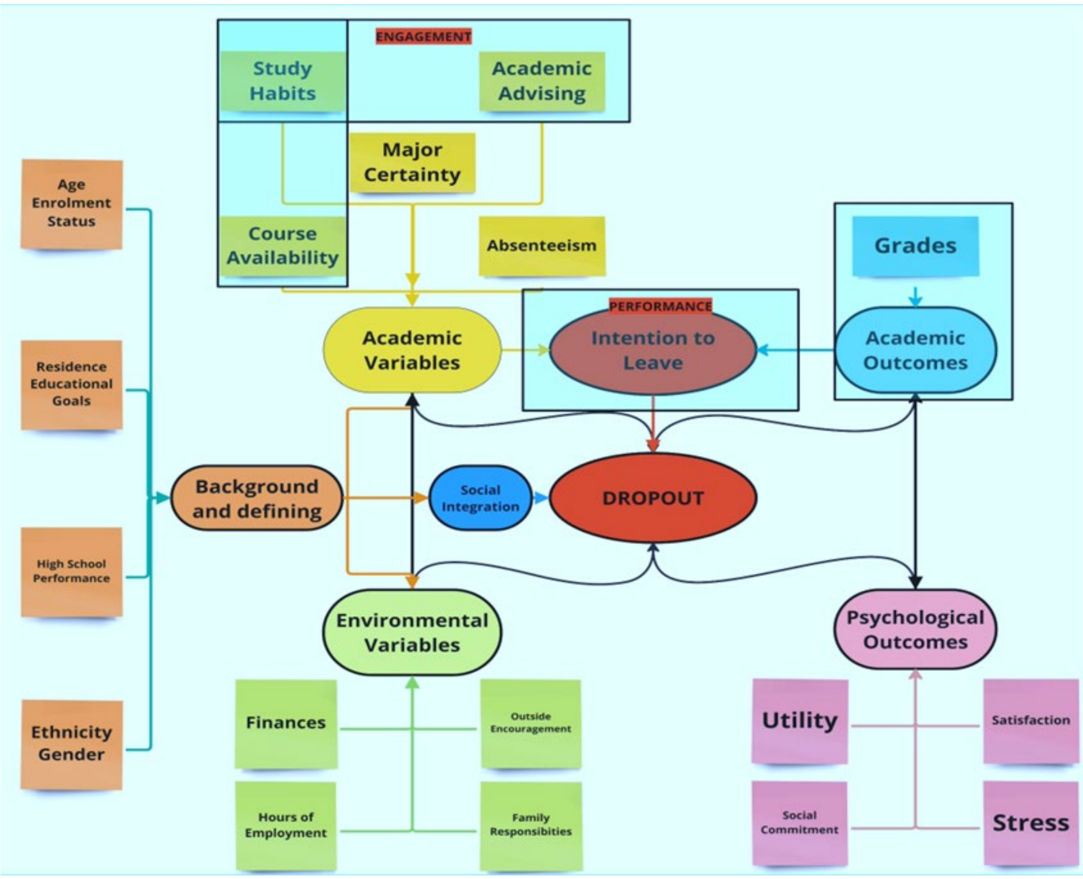

Figure 2-6 Concept of Retention-Adapted (Tinto, 1975)

The modified Theory of Student Retention, illustrated in Figure 2-6, relates to theories regarding student retention (Figueira, 2015). This theory of retention highlights the importance of engagement and grade performance.

2.4.2.1 Engagement: Tinto

The section "Engagement" in red reaffirms aspects concerning a student's activity level within a learning process. This section includes three key elements: course availability, study habits, and academic advice, which are some of the factors that define learning.

Study Habits: Pertains to effective time management, the proper conduct of study skills and habits, and consistency of students. Proper study skills are imperative success factors in learning; they are also a component of students' participation (Tinto, 2017).

Course Availability: This element relates to the issue of how free and diverse the courses are to the students. The availability of a wide selection of classes means that students can locate courses that interest them and cater to their academic ambitions, improving their morale and desire to excel (Schilling, 2009).

Academic Advising: This block represents the roles of Advisors, including mentoring, in the student's life. Students consult an advisor to enable them to make the right decisions concerning their courses, academic needs and even their life goals. For this reason, academic advising plays a significant part in satisfying the students' needs and participation in their educational processes (Campbell & Campbell, 1997).

Academic work environment variables hurt by student disengagement are absenteeism and certainty, which comprise the above engagement components. Therefore, students can attend classes and have confidence in the selected majors if they have established good study habits, are perceptive to the courses offered, and receive appropriate advice from the faculties (Dunn & Herron, 2023).

Each one of these engagement factors seeks to enhance Grades and Academic Outcomes, as indicated on the right side of the figure. Increased participation boosts the students' performance, comprehensively illustrated by improved grades and satisfactory academic achievement. The relationship between these constructs stresses the role of facilitating participation outcomes in educating (Tinto, 1999).

2.4.2.2 Engagement: Bean

In Figure 2-7 Concept of Student Attrition (Bean, 1980), engagement and performance are pivotal components of this theory: academic integration, social integration, and personal integration comprise engagement. Student effort, quality of effort, educational outcomes (grades) and learning comprise persistence. The engagement and performance link to the conceptual framework is evident.

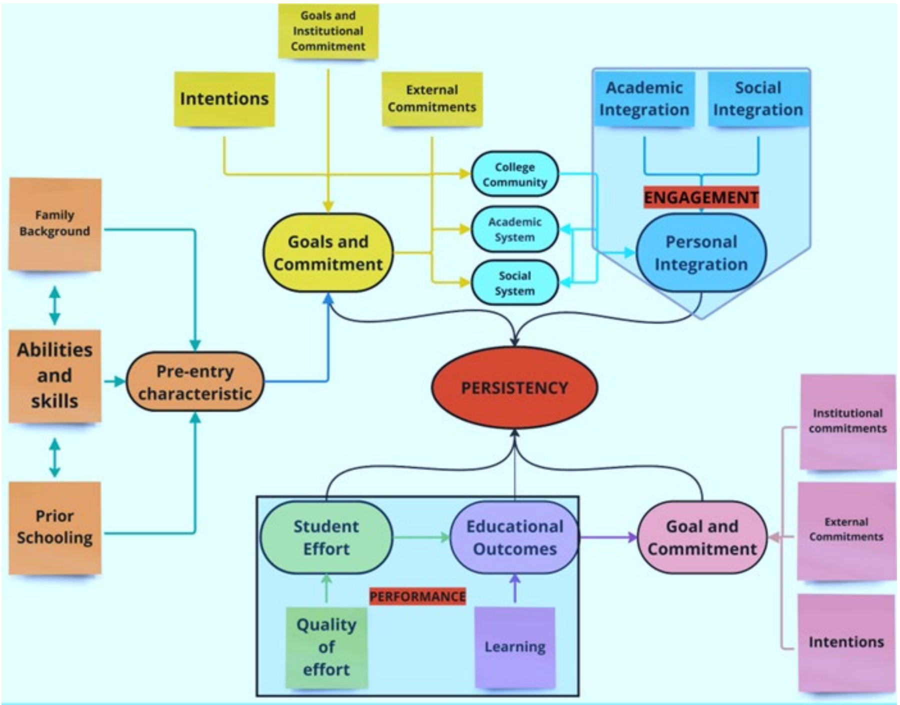

Figure 2-7 Concept of Student Attrition (Bean, 1980)

According to Bean's theory, engagement and performance are the main elements that lead to and explain student attrition. Figure 2-7 is an example of this concept elucidated by several related items. Engagement is closely associated with students' study habits (Bean, 1980). More engaged students develop effective study routines, positively impacting their academic success. According to Bean's theory, engagement comprises three main components: academic integration, social integration, and personal integration.

Academic Integration: Students engaged in their degrees are more likely to seek advice from registration and academic advisors to help them make the right majors or choose the most appropriate degree paths in job markets. Proactivity in seeking student recommendations to attain their objectives enables an improved combination of academic and career advancement. This proactiveness concerns how students feel a part of the university learning process or how relevant the university experience is to their learning. This relevance refers to their participation in the academic arrangements, their relationships with faculty and other university members, and how they fit in the educational system.

Social Integration: Engagement in social activities and networks on campus can enhance students' feelings of belonging and community, reducing the intention to leave. Social integration consists of the change that the student experiences with the social systems prevailing in the university, including interaction with fellow students, social sessions and the like. This change is aware that the interrelation between social life and university can enhance students' sense of affinity and attachment.

Personal Integration: Personal integration translates to the extent to which the individual has achieved a sense of order in that their goals and values match those of that institutional environment. It indicates the extent to which you, as a student, have assimilated yourself into the campus culture. It also relates to students' engagement in the available courses and their use of time and time management during their academic year, determined by the various activities in the university's academic calendar. It makes them victims of high engagement levels and arrows them in search of more initiative in their studies to fully maximise their multiple courses and academic progression processes.

2.4.2.3 Grades: Tinto

High-quality effort and good academic and social integration lead to effective learning and improved academic performance (Tinto, 2017). Performance is a measure of the educational outcomes achieved by a student, influenced by the learning process and the quality of effort invested (Lee, 2014).

In Tinto’s (1975) model, engagement and performance are fundamental for enhancing outcomes and ensuring student persistence. They are integral to fostering academic and personal integration, supporting students’ goals and commitments towards completing their education.

Feldman & Newcomb (2020, pp.627–657) hinted at the need for a "standard formula for measuring retention." Decades later, no such formula has gained universal acceptance. Despite extensive research and implementation of retention initiatives, universities still need help with retention rates (Shafiq et al., 2022). Tinto (1975) illustrates the concept of retention (persistency), as shown in Figure 2-20. Personal integration, academic system, social system, and academic and social integration are central to the study and were taken further by Bean (1980) with his Attrition theory.

The reasons behind student attrition are multifaceted and intricate, as presented by Bean (1980) and illustrated in Figure 2-7, which states that a comprehensive understanding of the underlying causes is needed to formulate effective strategies for intervention (Bean, 1988).

2.4.2.4 Grades: Bean

Performance in Bean's model includes student effort, the quality of effort, educational outcomes (grades), and learning. Many learning practices are determinants of study habits and course availability that define student grades, which underscore performance. Study skills and availability for different courses are vital in enhancing and determining the students' performance, as they show commitment and interest towards their academic pursuits.

Student Effort: This refers to the amount of time and energy a student dedicates to their studies and academic activities. Improved academic results often correlate with high effort levels (Carbonaro, 2005).

Quality of Effort: This measures how effectively students use their time and resources. Quality of effort is about studying efficiently, seeking needed help, and utilising available academic resources (Pace, 1982).

Grade Outcomes: Grades directly measure academic performance (Lynch & Hennessy, 2017). They are often used as indicators of a student's learning and mastery of course content (Allen, 2005; Carbonaro, 2005). High performance translates to good grades, which brings about positive academic direction and/or reconfirmation to pursue further education, thus reducing the chances of dropping out. Firm academic achievements help students stay focused and committed to achieving educational objectives, helping lessen the students' attrition rates (Allen, 2005). The intention to leave is because performance determines the level of satisfaction the learners have towards their academic programs and study experience – which determines their intentions to continue or discontinue their studies. High academic performance augments the satisfaction level and, thus, a more apparent commitment to press on with advanced learning. Conversely, harmful performance levels may foster dissatisfaction and result in dropping out of the learning process.

Based on Bean's (1980) paradigm, engagement and performance impact academic variables determining students' decision to persist or drop out. Engagement enhances the appreciation of course, material, and scholarly behaviour, while performance enhances a more excellent score and learner achievement. This enhancement reduces drop-out chances, and the overall psychosocial impact, such as satisfaction and stress level, is also increased.

2.4.2.5 Retaining Students with High-Impact Practices

Approximately one-quarter of students abandon their studies after the first year (Bork, 1999). Intervention programs can enhance retention rates, principally in the first year of studies (Kamer & Ishitani, 2021). Finding students who need support in advance is a priority to optimise the distribution of scarce resources towards intervention programs (Dos Reis & Yu, 2018).

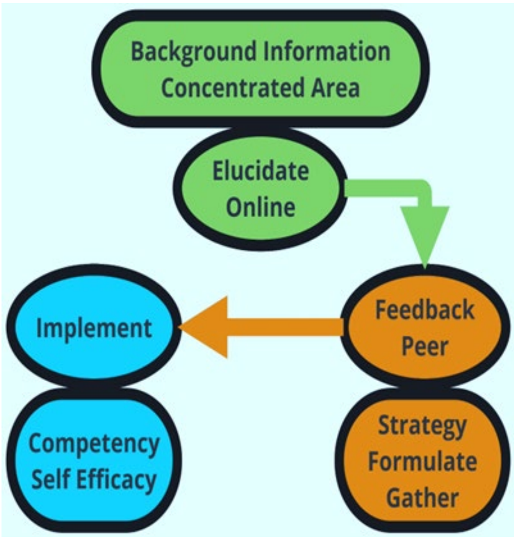

Figure 2-8 The Feedback Cycle (Flodén, 2016)

Integral to effective learning is student peer feedback (Flodén, 2016), as illustrated in Figure 2-8[4]. Due to this method's efficacy, learning and teaching settings embrace and research it more often (Topping, 2017). Recent systematic reviews and meta-analyses support its

4 . Topping (1998, p.250) describes feedback "as an arrangement in which individuals consider the amount, level, value, worth, quality or success of the products of learning of peers of similar status". I.e., reflective criticism, Falchikov (2003) refers to a peer group of the same status with whom one interacts. Falchikov (2003) says peer feedback improves academic performance and knowledge.

advantages. Applying peer feedback improves learning results over those without it. In addition, peer evaluations often match or surpass those of lecturers (Huisman et al., 2019; Double et al., 2020). Online peer feedback is becoming more common in learning and teaching technology. Institutions may encourage student achievement by introducing feedback methods that give students regular information on their performance (Xu et al., 2023).

The online feedback comments given should be closely related to the daily learning requirements of the students and used to improve their academic performance. Jongsma et al. (2023) found that online feedback is more effective than offline feedback when the outcome is measured rather than self-efficacy. However, peer review online has specific difficulties. Students may stop giving feedback to each other because they find it challenging to interact with one another in an online setting. In contrast, this conversation may help understand and respond to the comments (Guarda et al., 2023; Shi et al., 2023). Students can clarify or negotiate the meaning of the feedback they have received during feedback discussions (Zhu & Carless, 2018). They can also welcome feedback on the feedback they have given.

Early warning systems recognise students needing help, ensuring no student slips through the gaps (Trowler, 2010). Classroom assessment techniques also track and assess erudition development effectively. It is imperative to remember that supplying feedback to students is a top priority for universities because it is essential for success (Lomas & Nicholls, 2005). Research has shown active student partaking is crucial to learning and retention (Chen et al., 2022). Involving students in learning activities should be a top priority for learning and teaching communities during the first year of university when learning is most malleable (Friedman & Mandel, 2009). Students are inclined to learn innovative ideas and advance their intellectual capacities in group settings (Kember et al., 2023).

Delivering relevant learning experiences should be a top priority for institutions to provide a conducive environment for student learning and retention, which is foundational for student success (Bean, 1980). The institutions should tailor these experiences to align with students' interests, career aspirations, and prior experiences to keep them engaged and motivated. Institutions can achieve this goal by linking the curriculum to real-world applications, for instance, through internships and service learning. To promote student success, institutions should prioritise supplying five conditions: generating appropriate learning experiences, student engagement, regular feedback, and learning and social support mechanisms and indicators of at-risk students (Pendakur, 2023).

The conditions, however, have a weakness within them, as they assume that all the students start from the same background when they enter a university. Students with varying levels of academic preparation may face distinct challenges and require different forms of support to succeed. Thus, educators and administrators should consider the diversity of students' backgrounds and experiences when designing interventions to support student success (Kember et al., 2023).

Various papers have empirically validated Tinto's model. For instance, Cabrera Nora & Castaneda (1992) discovered that students who perceived elevated academic and societal assimilation levels were likelier to persevere in their studies than those who did not (Pascarella & Terenzini, 1979). Students who committed to their institution had more potential to continue than those who did not. (Kuh et al., 2008) found that institutions that implemented strategies to enhance student engagement and involvement had higher retention rates than those that did not. Brownell & Swanersec (2009 sec.Abstract) state, “Tinto (1975) deposited his theory about student integration into the academic and social system of the higher education providers, Tinto suggested a multidimensional component which underlined the higher education community engaging students in all aspects of higher education including academic and non-academic. Tinto's theory basically hypothesises that persistence is determined by the match between an individual's motivation and academic ability and the institution's academic and social characteristics. A second and major model is Bean's (1986) student's intention to stay or leave into the attrition model, derived from psychological theories and based on attitudinal research of Ajzen and Fishbein (1972) which later developed by Bentler and Speckart (1981). Key ideas from the model suggest that a strong association was related to intentions and behaviors and that an undergraduate student decision to persist or drop out was strongly related to affect. One conclusion about student engagement was students need to be satisfied and academically prepared especially those in the first years to achieve success and maintain continuous enrollment in higher education (Astin, 1985; Tinto, 2005; Kuh, 2001, 2007). Tinto's integration theory has received considerable validation of non-academic factors and impacting student continuation (Pascarella & Terenzini, 1977; Terenzini & Pascarella, 1977; Chapman & Pscarella, 1983; Pascarella & Chapman, 1983). The latter model has received empirical validation and support based on a large number of studies that looked at background information as the socioeconomic levels of students' families and its effect on postsecondary continuation in higher education (Astin & Oseguera, 2004; Sewell & Shah, 1968). With the large number of studies coming from the United States (US) and other Western countries (Kenny & Stryker, 1994; Dekker & Fischer, 2008) have underlined the differences on how students develop and internalise beliefs, needs, and wants that in turn impact academic motivation to persist and succeed in higher education. While few studies have emerged from the Middle East, the recent establishment of the Middle East and North Africa Association of Institutional Research has prompted many researchers in this area to seek the understanding and experiences of students in higher education".

Experts have suggested strategies that align with Tinto's model of student retention. It includes cultivating a learning environment among students, interfering with faculty-student relations, and providing opportunities to engage in on-campus activities among students. Figure 2-7 of Bean's (1980) developed a student attrition model that explains that student dropout is not one dimensional or triggered by only one factor but is complex and caused by background factors, academic aptitude, environmental aspects, and social adjustment. These factors impact students' ability to learn and retain information and their psychological health, thus prompting dropout. Brownell & Swanersec (2009 sec.Abstract) found, "In AAC&U's 2007 report, College Learning for the New Global Century, the National Leadership Council for Liberal Education and America's Promise (LEAP) identified several innovative, "high-impact" practices gaining attention in higher education. In a subsequent AAC&U report, Kuh (2008) describes strong positive effects of participating in high-impact activities as measured by the National Survey of Student Engagement (NSSE)… culminating experiences reported greater gains in learning and personal development. These gains included "deep approaches" to learning, which encompass integrating ideas and diverse perspectives, discussing ideas with faculty and peers outside of class, analysing and synthesising ideas, applying theories, judging the value of information as well as one's views, and trying to understand others' perspectives. According to Kuh, "Deep approaches to learning are important because students who use these approaches tend to earn higher grades and retain, integrate, and transfer information at higher rates". Kuh's Engagement Theory posits that student success is directly related to student engagement and that institutions can foster this engagement through specific educational practices. This theory aligns well with the thesis focus on AI-facilitated peer-to-peer learning and its impact on student engagement and academic performance.

The merits stemming from massive open online courses (MOOCs) include flexibility and increased student acceptance (Borrella et al., 2022). Nevertheless, numerous online course choices increase the complexity of defining course materials (Chen & Chen, 2015). Using AI can be a good solution as it allows each learner a course and activity according to their preferences and abilities. In this area, such an issue can make an impact by availing learning experiences to help a student in the learning process, allowing the student to gain better results in their learning endeavours. For better learning process effectiveness and learners' satisfaction, AI can offer material which corresponds to the course's purpose. Therefore, due to AI's key feature of customizability of educational resources, the method discussed in the present work can have great potential for increasing retention levels and, therefore, the performance indicators of students.

In addition, intelligent tutoring systems can monitor when students are no longer interested in a course and inform educators before disengagement can occur (Kurni et al., 2023). In some ways, integrative management has proved beneficial for executing the strategy, such as increased student participation, better outcomes for group work and study, and better levels of satisfaction among students regarding the process of learning (Ouyang, Wu, Zheng, et al., 2023)[5].

The guidelines developed by Spady (1970), Tinto (1975), & Bean (1980) form the conceptual framework for the analysis of student retention and necessary factors that lead to improvement of performance. Based on these theories, this research seeks to understand university students' learning processes and social interactions. Two points support the consideration of this theoretical framework. The conceptual framework forms a good starting point for analysing learner retention based on learning and teaching. Second, the method it applies to study learners' retention rates is holistic, considering each learner's journey and academic performance. Lack of academic and social support, like tutoring and mentoring, raises the probability that the learners may not complete their course. The high-impact practices and seminal frameworks inform the research questions.

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5 According to the Education White Paper 3, More access to higher education is expected to increase success and completion rates, particularly for female and Black students, according to the South African Programme for the Transformation of Higher Education. However, despite this expectation in 2002, the Department of Education saw a troubling decrease in retention rates and an increase in dropout rates. The Minister of Education in South Africa addressed this issue in a speech on May 15, 2005, highlighting that half of the cohort of students admitted in 2000 had dropped out by 2003 and at a September 2005 forum on higher education adaptation at the University of the Free State, the Chief Executive Officer of the Council on Higher Education further emphasised the need to enhance throughput and graduation rates by improving efficiency and decreasing dropout rates. The Deputy Director General of the Department of Education echoed these concerns and reported that 50% of students who register for higher education courses do not complete them (City Press, 2005). In 2006, the Free State Provincial Government drew attention to the substantial failure levels of students in the Faculty of Health Sciences at the University of the Free State, with students of colour experiencing attrition rates as high as 70%. Consequently, this led the Minister of Education, at a conference in 2006, to encourage a critical evaluation of the senior education system. Immediate action is needed to tackle the issue of high attrition rates and low retention rates in South African higher education institutions, particularly among underrepresented groups.

2.5 Link between Research Questions and Theoretical Frameworks

By mapping each research question to the theoretical frameworks, a more explicit connection between the research questions and the theoretical frameworks is drawn—Tinto's Retention Theory and Bean's Theory of Attrition. Table 2-2 summarises how the research questions connect with Tinto's Retention Theory and Bean's Theory of Attrition.

Table 2-2 Tabulated summary of how the research questions connect with Tinto's Retention Theory and Bean's Theory of Attrition

Research Questions	Theoretical Framework	Connection
Main Research Question (MQ): To what extent does Peer-to-Peer AI support influence student engagement, grades, and pass rates?	**Tinto's Retention Theory** **Bean's Theory of Attrition**	**Tinto's Retention Theory:** Engagement and academic integration are crucial to retention. Peer-to-peer AI support fosters these aspects, leading to better retention and grades. **Bean's Theory of Attrition:** Students' perceptions and experiences are critical. AI support improves perceptions, enhances academic outcomes, and reduces attrition.
Sub-Question 1 (RQ1): How do students perceive the influence of AI-facilitated peer-to-peer support on engagement as part of their belief system?	**Tinto's Retention Theory** **Bean's Theory of Attrition**	**Tinto's Retention Theory:** Engagement is vital for retention. AI support enhances student engagement, aligning with Tinto's academic and social integration focus. **Bean's Theory of Attrition:** Perceptions influence retention. Any positive perceptions from AI support align with Bean's emphasis on belief systems, leading to reduced attrition.
Sub-Question 2 (RQ2): To what extent does AI-facilitated peer-to-peer support enhance student grades by assisting students in their return?	**Tinto's Retention Theory** **Bean's Theory of Attrition**	**Tinto's Retention Theory:** Grades are a vital retention determinant. AI support that improves grades aligns with Tinto's model by enhancing academic integration. **Bean's Theory of Attrition:** Grades correlate with student satisfaction. Improved grades through AI support increase satisfaction, reducing dropout rates.

Research Questions	Theoretical Framework	Connection
Sub-Question 3 (RQ3): To what extent does AI-facilitated peer-to-peer support influence pass rates?	**Tinto's Retention Theory** **Bean's Theory of Attrition**	**Tinto's Retention Theory:** Pass rates are tied to retention through academic success. AI support that improves pass rates strengthens academic integration, enhancing retention. **Bean's Theory of Attrition:** Pass rates correlate with retention. AI support that boosts pass rates provides a practical solution to lower attrition, aligning with Bean’s theory.

These theories inform the research questions as follows:

Main Research Question (MQ): To what extent does Peer-to-Peer AI support influence student engagement, grades, and pass rates?

Theoretical Connection:

- **Tinto's Retention Theory** emphasises the role of student engagement and academic integration in retention. The theory posits that students who are more engaged and feel integrated within the educational environment are likelier to persist and achieve better grades and pass rates. Peer-to-peer AI support, which fosters engagement and integration through personalised and adaptive learning environments, can thus be directly linked to the retention outcomes predicted by Tinto.
- **Bean's Attrition Theory** highlights the influence of students' perceptions and personal experiences on their decision to stay or leave. Peer-to-peer AI support can influence these perceptions by improving academic experiences (grades and engagement) and reducing the likelihood of attrition.

Sub-Question 1 (RQ1):

How do students perceive the influence of AI-facilitated peer-to-peer support on engagement as part of their belief system?

Theoretical Connection:

- **Tinto's theory suggests that engagement is a critical factor in retention and is** influenced by students' academic and social integration. Students' perceptions of AI-facilitated peer support, which enhances engagement, align with Tinto’s emphasis on the importance of integration for positive educational outcomes.
- **Bean’s Theory** further adds that students' beliefs and perceptions significantly influence their engagement and retention. AI support that enhances these beliefs through tailored feedback and interaction would thus align with Bean’s framework, explaining how positive perceptions can reduce attrition.

Sub-Question 2 (RQ2):

To what extent does AI-facilitated peer-to-peer support enhance student grades by assisting students in their return?

Theoretical Connection:

- **Tinto's Retention Theory** posits that academic performance, which includes grades, is a significant determinant of student retention. As suggested by Tinto's model, AI-facilitated peer support systems that help students return to academic focus and improve their grades would directly impact retention.
- **Bean's Theory** correlates academic outcomes, such as grades, with student satisfaction and persistence. Higher grades, achieved through AI-facilitated peer support, would increase satisfaction and reduce attrition rates.

Sub-Question 3 (RQ3):

To what extent does AI-facilitated peer-to-peer support influence pass rates?

Theoretical Connection:

- **Tinto's Theory** connects academic integration and success, such as pass rates, with retention. AI support systems that help students achieve passing grades can thus be seen as enhancing the academic integration process, leading to higher retention.

- **Bean's Attrition Theory** supports that academic success, reflected in pass rates, reduces the likelihood of student dropout. AI-facilitated support that improves pass rates would align with this theory, providing a practical intervention to lower attrition.

Although the research questions and theory are well-connected, contradictions in AI may still impact learning and performance.

2.6 AI Contradictions and Learning

Most research in artificial intelligence focuses on solving the following paradox: Deep learning methods are general. They can be implemented in many research areas because the principles of mathematics and algorithms involved are general implementations and transfers of previously learned results. On the other hand, learning how to solve a particular task demands qualitatively labelled data, which can be made very accurate with original algorithmic approaches and correct tuning of hyperparameters (Kornaev et al., 2022).

As implemented as a peer-to-peer support tool, AI could be a valuable strategy for tackling problems arising from poor student participation, underachievement, and dropout rates in the face of the paradox of AI research. The dilemma is that deep learning methods are both general and specific. While based on fundamental mathematical concepts, they require task-specific data and precisely tuned algorithms for optimal performance. Educational settings may leverage this paradox to create adaptive and personalised learning environments. AI-powered peer support systems could utilise deep learning's generalisability to develop models that recognise patterns in student behaviour, identify engagement levels, and predict potential dropout risks. Fine-tuning these systems with data from specific educational contexts might more effectively tailor the support to individual student needs. For example, AI could facilitate peer learning by matching students with complementary strengths and weaknesses and forming study groups that may enhance each student's potential. It might also monitor interactions within these groups, offering real-time feedback and interventions when necessary, potentially improving engagement. By providing personalised assistance and fostering a collaborative learning environment, AI may help students stay motivated, perform better, and remain committed to their academic journey, ultimately contributing to improved retention rates. AI's ability to generalise across different tasks while customised for specific educational outcomes may effectively bridge the gap between broad applicability and precise, targeted support. This positions AI as a potentially valuable tool for addressing student engagement, performance, and retention challenges in higher education. Understanding the evolution of the AI landscape provides the context of this study.

2.7 Exploring the AI Landscape

As Benko & Lányi (2009) presented, the theoretical history of AI and computer-based learning and teaching reflects continuous exploration and development. It approaches to enhance learning experiences and promote individualised learning, as illustrated in Table 2-3. Due to these elements, computer-based learning and teaching have gained popularity among students and educators (Baek et al., 2023).

Table 2-3 Key Elements of AI

Key features of AI
The interactive nature of this medium engages and involves students of all ages and grades.
Students can go ahead independently and choose alternative teaching strategies and presentation methods.
The system supplies detailed feedback on individual student progress, which helps lecturers and authors evaluate and change lessons and measure overall learning and teaching effectiveness.
Facilitators can prepare and change lesson content with little training in the language and without any prior programming experience.
Session materials can be compiled or changed at a student workstation anywhere, allowing facilitators in participating institutions to modify materials according to the unique needs of their students.

The gap between learning and teaching research and practical learning and teaching applications in different environments is a significant challenge (Tate et al., 2023). In some cases, AI research focuses on theoretical models and experimental prototypes developed in isolation from real-world applications' specific needs and constraints (Bork, 1999). A further consideration is a need for more standardisation in AI research and development. Several techniques and models define AI in education, which makes it challenging to compare and evaluate different approaches used in the field (Chew et al., 2017).

Another area that needs further discussion is the applications of AI, as it is present in many branches (Bork, 1999). Despite this discussion focusing on various aspects of adaptive AI and its role in learning and teaching, nothing can be more important than acknowledging its impact on other industries, including healthcare and finance. Technology, specifically artificial intelligence, has changed healthcare practices by diagnosing fatal diseases, forecasting future health tendencies, and inventing possible cures (Sallam, 2023). This transformation capacity calls for extending awareness of the reality of AI to various disciplines for their potential positive assimilation.

The section raises an issue between the possibility of en masse education and an escalating cost of personalised learning (Glotova et al., 2023). This cost of personalisation is a clear indication that while delivering an individual learning and teaching strategy may be effective, it might be costly to implement (Minn, 2022). An example of such a solution is using adaptive learning technologies that provide students with more individual and focused interactions than are likely given in this fast-paced course but do not depend on the traditional tutorial system.

AI's effect is becoming more sociologically and ethically problematic (Lim et al., 2022). Where they are widespread and effective, there is the danger that they may bring bias and discrimination in human decision-making and encroach on individuals' right to privacy and self-governance (Larsen & Emmett, 2023). Thus, these problems make it necessary to develop policies and procedures addressing ethical concerns in AI as peer-to-peer support.

Prevailing learning models assume that learning is a process of information transfer from teacher to student. Evaluation of learning often relies on memory recall, employing ineffective methods such as multiple-choice tests. The models must consider students who do not learn or only learn partially through this information-transfer method, thus overlooking high-level skills like problem-solving. This model is inadequate for the future, and alternatives must be explored (Bork, 1999).

Individual mastery should be the learning goal, as students have different interests, backgrounds, and learning styles, leading to varied learning rates. Current learning and teaching structures do not support individual pacing and drastic changes to these structures. Another major challenge is the lack of equity in learning opportunities (Bright & Calvert, 2023). Although students enjoy outstanding learning opportunities, many face barriers, particularly those from underprivileged backgrounds (Bright & Calvert, 2023). An urgent need is to establish a more equitable learning landscape (Akiva et al., 2023)

New models of learning can lead to further learning structures that are continuous, self-paced, and mastery-based; as per Bloom (1984) & Tuomi (2023), they have highly interactive learning experiences where everyone learns everything to the mastery level, making grades obsolete. Tuomi (2023) conducts frequent checks for mastery and offers alternative learning sequences to students who have not mastered the material. Learning and evaluation become a unified process, avoiding the problem of cheating.

Additionally, questions arise about how innovations can combine research and practice to facilitate unremitting improvement and how technology can foster a cost-efficient individualised learning experience (Epstein et al., 2013). These challenges emphasise the tension between the cost-effective traditional mass learning and teaching system and the more expensive emerging trend towards personalised learning and teaching (Tran & Campbell, n.d.) It is crucial to note that the term AI encompasses various methods, algorithms, and techniques that aim to create machine intelligence or learn from data, embracing statistical learning, machine learning, deep learning, expert systems, and data science (Chen et al., 2022).

In such an interactive environment, learning can be constructivist, meaning students can discover knowledge through guided discovery (Kor et al., 2023). The learning material must be intrinsically motivating and personalised to keep students engaged, and frequent evaluation is needed to ensure that students stay focused (Walkington, 2013). Small group work or parent involvement can also supply opportunities for human contact. Thus, it is possible to state that information on the types of AI is necessary for integrating this concept into the learning and teaching process.

2.7.1 Types of Artificial Intelligence

The introduction of AI in educational research has presented possibilities for investigating deeper and more complex learning and teaching issues (Chen et al., 2022). According to Haenlein & Kaplan (2019), this process shows ways of learning through technology. This approach identifies effective strategies and tailors educational experiences to meet individual student needs. Nonetheless, there are still challenges in effectively translating research findings into practical implementation to enhance learning outcomes (Goldrick-Rab, 2010; Li et al., 2021). Additionally, there is a need to develop cost-effective and functional approaches to deliver personalised learning experiences (Holmes et al., 2023). Different learning and teaching technology types, such as digital adaptive learning tools, offer real-time responses to students' interactions by autonomously supplying individualised support.

The emergence of artificial superintelligence will change humanity, but not soon (Rees, 2021). The history of artificial intelligence (AI) is a journey through time, marked by significant milestones and innovations, as illustrated in Table 2-4. It traces back to ancient times when Alexander Heron designed automatons powered by water and steam. In the 17th century, Wilhelm Schickard created a mechanical calculator, followed by Gottfried Leibniz's creation of a binary counting system in the 1670s, laying the groundwork for modern computers. In the 1820s, Charles Babbage made a name for himself by inventing a mechanical calculator. Significantly, the term "robot" is derived from the Czech word 'robota' or forced labour and was created by Karel Capek in 1923. The 1930s witnessed the construction of Konrad Zuse's Z1, a programmable computer, and the 1950s brought Alan Turing's Turing Test, the Mark 1 device with AI programs, and the development of LISP by John McCarthy. In the 1960s, PLATO's adaptive tutoring system and Weizenbaum's ELIZA language processing program emerged. The 1970s saw the inception of TCP/IP protocols and the birth of the Internet. Herbert Simon's Nobel Prize in 1978 celebrated his work on limited rationality in simulated intelligence. In 1997, the supercomputer Deep Blue defeated chess champion Kasparov. Advancements continued with Honda's Asimo in 2005, highlighting remarkable human-like abilities. By 2010, mind power controlled Asimo. Boston Dynamics introduced Big Dog and Atlas in 2013. Facebook's Deep Face and Google's acquisition of DeepMind made headlines in 2015. Finally, the publication of OpenAI's GPT-3 in 2021 signalled the subsequent development and ongoing growth of artificial intelligence.

Table 2-4 Chronological History of Artificial Intelligence

Year	Development
Ancient Times	During antiquity, Alexander Heron designed automatons powered by water and steam.
1623	Wilhelm Schickard created a mechanical calculator that could perform basic arithmetic tasks.
1672	Gottfried Leibniz advanced a binary counting system as the fundamental basis for modern computers.
1820s	Charles Babbage is renowned for inventing a mechanical calculator.
1923	Karel Capek coined the term "robot".
1936	Konrad Zuse built the Z1, a programmable computer with 64K memory.
1950s	Alan Turing introduced the Turing Test, and the Mark 1 device was the first to have artificial intelligence programs. Newell, Shaw, and Simon developed the Logic Theorist, the first AI system to solve math problems. John McCarthy created LISP, a significant language in AI development.
1960s	Donald Bitzer *et al.* developed the PLATO adaptive tutoring system, and Weizenbaum developed an ELIZA language processing program.
1973	The TCP/IP protocols were first developed in 1973 (Rosker et al., 2009).
1974	The creation of the Internet.
1978	Herbert Simon obtained a Nobel Prize for his contributions to the notion of bounded rationality, which is vital to simulated intelligence.

Year	Development
1997	In a historic event, the supercomputer Deep Blue defeated the world-renowned chess player Kasparov.
2005	The introduction of Asimo marked a significant advancement in the development of robots that closely emulate human abilities and skills, bringing them closer to artificial intelligence.
2010	Asimo was programmed to be controlled by the power of the mind.
2013	Boston Dynamics created the four-legged robots Big Dog and Atlas.
2015	Facebook announces Deep Face; Google buys Deep Mind.
2021	Open AI GPT3 is released

AI with superintelligence may be the last creation of humanity. Creating an AI type that is so advanced that it can generate AI beings with even higher intelligence could fundamentally alter human invention (Shin et al., 2023). Such beings would be intelligent beyond human comprehension and capable of superhuman feats (Shin et al., 2023). How near are we to developing AI that can think more complexly than humans? The short answer is no, but the speed has accelerated since the 1950s when the modern field of AI first emerged (Gillis, 2023). As computer scientists, mathematicians, and specialists in other fields improved the algorithms and hardware in the 1950s and 1960s, artificial intelligence (AI) made rapid advancements (Kubassova et al., 2021). The objective of creating a thinking machine comparable to the human brain proved challenging, and interest in the topic dwindled despite early claims by AI pioneers (Anderson et al., 2018). While generative AI has advanced quickly in recent years, super-intelligent AI still needs to catch up (Larrey, 2017). Generative AI, trained on extensive data, generates text, images, and audio with near-human quality (Lin et al., 2023). The AI program must determine whether the data it gives a user is up-to-date or whether the counsel it offers is accurate (Gillis, 2023).

Table 2-5 Types of AI (Gillis, 2023)

Narrow AI		Powerful AI	
Reactive AI	**Limited memory**	**Theory of mind**	**Self-aware**
• Simple classification and pattern recognition tasks. • Scenarios where parameters are known to beat humans because they can make calculations much faster. • Incapable of dealing with scenarios including imperfect information or requiring historical understanding.	• Can manage the complex classification of tasks. • The capability to forecast future occurrences based on historical data. • Capable of performing complex tasks such as self-driving automobiles, yet susceptible to outliers. • The current state of AI is that we have hit the wall.	• Able to understand human motives and reasoning: can deliver a personal experience to everyone based on their reasons and needs. • Able to learn with fewer examples because it understands motive and intent. • Considered the next milestone for AI's evolution.	• Human-level intelligence can bypass our intellect, too. • It is considered a long-shot goal.

But what distinguishes super-intelligent AI from our current generative AI models? One can classify AI using capabilities or functionality (Lin et al., 2023). Based on functionality, there are four primary types of AI. The first two types fall under the umbrella of narrow AI, defined as AI trained to conduct a limited range of activities. The third and fourth varieties, frequently called powerful AI, are still being developed (Trivedi, 2023). Table 2-5 illustrates the types of AI that have led up to the new reality and further discusses them.

2.7.1.1 Reactive AI

Reactive AI algorithms are only capable of working with current data. Because this kind of AI lacks a specific functional memory, it cannot draw on the experiences of the past to guide its current and future decisions. AI and machine learning models exhibit this. These models, which have their roots in statistical math, may consider enormous data sets and generate a result that appears intelligent. Reactional or reactive AI is this type of technology, and there are fields where it outperforms humans. Most notably, in 1997, IBM's reactive AI Deep Blue defeated Garry Kasparov. Spam filters and recommendation engines both benefit from this kind of AI. Reactive AI is severely constrained. However, real-life actions are not reactive because we may not have all the knowledge we need to react in the first place (Gillis, 2023). Even with incomplete information, humans are masters of anticipation and can plan for the unexpected

(Montgomery, 2023). For various use cases, from natural language comprehension to self-driving cars, this vague information scenario has been one of the target milestones in the advancement of AI (Hafner et al., 2023). Because of this, scientists attempted to create the next stage of AI, which includes the capacity for limited memory machines for learning.

2.7.1.2 Limited memory AI

AI with limited memory can temporarily store info from past experiences (Hafner et al., 2023). The profound learning revolution began in 2012 (Gillis, 2023). An algorithm mimicking neuron linkage in the human brain was developed based on our understanding of its workings (Daimari et al., 2023). Deep learning becomes more intelligent with increased data for training (McDonnell & Crivac, 2023). Deep understanding significantly increased AI's capacity for picture identification, and additional classes of AI algorithms quickly emerged, including deep reinforcement learning (Shen & Chang, 2023). These AI models better absorbed the properties of their training data, but more crucially, they got better over time.

A famous instance is Google's AlphaStar project, which won the real-time strategy game StarCraft II against top-tier professional players (Elmaraghy et al., 2023). The models operate in incomplete data environments. To refine tactics and judgment, AI continuously competes against itself (Elmaraghy et al., 2023). A player's early choices in StarCraft may have significant consequences later. As a result, the AI needed to foresee how its actions would turn out long in advance. A similar idea is evident in self-driving cars, where the AI must forecast the course of neighbours (Bautista & Mester, 2023). These systems use past data as the foundation for AI's decision-making. Reactive machines obviously couldn't manage these kinds of circumstances. Natural language processing, chatbots, and virtual assistants frequently employ AI with little memory. Despite all these developments, AI still needs to catch up to human intelligence (Shiffrin & Mitchell, 2023). The need for enormous amounts of data is the most notable (Grassini, 2023). Although models can improve through retraining, altering the AI's initial training environment necessitates training from scratch (Griffiths, 2019). Consider learning a language as an example: Learning a second language simplifies learning a third and fourth language (Elmaraghy et al., 2023). There is no difference for AI (Gillis, 2023). The limitation of focused AI emerges clearly: it excels at one task but fails dramatically on other tasks when altered (Gillis, 2023).

2.7.1.3 Theory of the Mind AI

The ability of an AI system to assign mental states to different entities is referred to as the theory of mind capabilities (Mao et al., 2023). The concept derives from psychology and calls for AI to infer the intentions and motives of entities, such as their beliefs, feelings, and objectives (Bharadwaj et al., 2023). This kind of AI has yet to be created (Gillis, 2023).

By examining speech, images, and other data types, emotion AI seeks to understand, replicate, monitor, and react correctly to human emotion (Tantray, 2023). Despite its potential use in healthcare services and advertising in this capacity, it is still far from one that an AI with a theory of mind would have overcome (Haring et al., 2023). The latter can comprehend people and change how they are treated, depending on how well they gauge their emotional state (Tantray, 2023).

One of the most significant obstacles to AI is understanding moods (Shiffrin & Mitchell, 2023). The kind of AI capable of producing a masterpiece portrait is nonetheless oblivious to the subject it has depicted (Jarrahi et al., 2023). It can create lengthy articles without understanding a single word of what has been written (Goldstein & Kirk-Giannini, 2023). An AI that has achieved the theory of mind condition would bypass this restriction (Gillis, 2023).

2.7.1.4 Self-Aware AI

Precursors to self-aware or conscious computers, or systems that are aware of both their internal state and that of others, are the various varieties of AI discussed above (Ott, 2023). This internal state refers to artificial intelligence that can replicate human emotions, desires, and requirements. The internal state, however, is a far-fetched aim for which we need both the hardware and the algorithms (Gillis, 2023).

In the future, it will be possible to determine whether artificial general intelligence (AGI) and self-aware AI are related (Latif et al., 2023). “AGI refers to creating (semi-)autonomous, adaptive computer systems with the general cognitive capabilities typical for humans. The ability to support abstraction, analogy, planning and problem-solving” (Voss & Jovanovic, 2023: 1). We still need to learn more about it to create an artificial brain that is even close to being as intelligent as the human brain (Gillis, 2023).

2.7.1.5 Additional: Narrow, general and super-AI

AI develops quickly, leading to labels for diverse kinds of AI by people still working to establish them (Yetisensoy & Rapoport, 2023). However, no agreement exists on what these expressions signify, making it difficult to understand what AI can and cannot do (Papko, 2023).

The following term frequently refers to the four forms of AI mentioned above: AI or limited AI (Lee et al., 2018). The most prevalent kind of AI currently in use is known as narrow AI because it trains to complete a specific task more quickly (Voss & Jovanovic, 2023). Weakness refers to the AI's lack of human-level general intelligence (Voss & Jovanovic, 2023). Siri, Alexa, driverless vehicles, chatbots, and other forms of limited AI, as well as recommendation engines, are examples.

General artificial intelligence is the ideal AI, which would be able to work as effectively as a human, and it would be able to understand, learn, and behave similarly to a human (Voss & Jovanovic, 2023).

Superintelligence-simulated AI is self-aware AI with cognitive capabilities above and beyond humans (Shin et al., 2023). Super intelligent AI can reason, judge, learn, and think (Larrey, 2017). In comparison to humans, artificial superintelligence would be vastly superior in every task since it would have unlimited access to memory, processing power, and analysis tools (Lee et al., 2018).

2.7.2 Relevance of AI Types to Research Questions

Table 2-6 articulates how each type of AI could influence the research questions, linking the technical aspects of AI to the educational outcomes.

Table 2-6 Summary of the relevance of different AI types (Reactive AI, Limited Memory AI, Theory of Mind AI, Self-Aware AI) to your research question

AI Type	**Description**	**Relevance to Main Research Question (MQ) Peer-to-Peer AI Support's Influence on Engagement, Grades, and Pass Rates**	**Relevance to Sub-Question 1 (RQ1) Student Perceptions of AI-Facilitated Support on Engagement**	**Relevance to Sub-Question 2 (RQ2) Enhancement of Student Grades by AI-Facilitated Support**	**Relevance to Sub-Question 3 (RQ3) Influence of AI-Facilitated Support on Pass Rates**
Reactive AI	Basic AI systems that respond to specific stimuli without learning from past experiences. Example: Simple chatbots or recommendation engines.	Reactive AI can enhance student engagement by providing immediate, context-specific responses or recommendations that support learning needs.	Limited impact on perceptions of engagement as it cannot adapt over time, potentially leading to repetitive or predictable interactions.	Reactive AI may improve grades by providing timely responses or resources, though limited by a lack of adaptation to student progress.	Minimal influence on pass rates due to its inability to learn from past interactions or improve over time.
Limited Memory AI	AI systems that can learn from past experiences to improve future interactions. Example: AI in adaptive learning platforms.	Limited Memory AI can increase engagement by adapting content based on student interaction history, creating a more personalised learning experience.	Enhances perceptions of engagement through adaptive responses and learning, fostering a more interactive experience.	There is more significant potential to improve grades through personalised support, as the AI adjusts content and feedback based on prior student performance.	Positive impact on pass rates by continuously adapting to students' learning paths, providing more effective support over time.
Theory of Mind AI	Advanced AI that can understand and simulate human emotions, beliefs, and intentions.	Theory of Mind AI could significantly boost engagement by understanding and responding to	It is highly relevant to perceptions of engagement, as this AI type can interact more human-likely and empathetically	Strong potential to enhance grades by providing tailored support that considers students'	It could significantly influence pass rates by offering support that aligns with students' motivations

AI Type	Description	Relevance to Main Research Question (MQ) Peer-to-Peer AI Support's Influence on Engagement, Grades, and Pass Rates	Relevance to Sub-Question 1 (RQ1) Student Perceptions of AI-Facilitated Support on Engagement	Relevance to Sub-Question 2 (RQ2) Enhancement of Student Grades by AI-Facilitated Support	Relevance to Sub-Question 3 (RQ3) Influence of AI-Facilitated Support on Pass Rates
		students' emotional and cognitive states.	, improving the learning experience.	emotional and cognitive states, leading to better academic outcomes.	and emotional needs, reducing dropout rates.
Self-Aware AI	AI possesses self-consciousness and an understanding of its existence. It is currently theoretical and not yet realised.	While currently theoretical, Self-Aware AI could potentially revolutionise engagement, grades, and pass rates by autonomously adapting and evolving to meet student needs.	This could lead to highly personalised engagement strategies, as the AI would continuously evolve its approach based on deep self-awareness and understanding of the student.	Theoretically, it could improve grades by autonomously identifying and addressing learning gaps, though this is speculative.	Potentially transformative for pass rates by providing highly adaptive and evolving support that could foresee and address student challenges.

A concise narrative for each AI type, linking them to the research questions:

- **Reactive AI**: Reactive AI, like simple chatbots, responds to specific stimuli without learning from past interactions. It can enhance student engagement by providing immediate, context-specific responses or recommendations. However, its limited adaptability may reduce its effectiveness in long-term engagement, grade improvement, and pass rates.

- **Limited Memory AI**: Limited Memory AI learns from past interactions to improve future responses. This adaptability can increase student engagement by personalising content and support. As it adjusts to individual learning paths, it may and could positively influence grades and pass rates by offering more effective, tailored assistance over time.

- **Theory of Mind AI**: Theory of Mind AI understands and simulates human emotions and intentions, enabling it to interact more empathetically with students. This human-like interaction can significantly enhance student engagement and perceptions of support. Considering students' emotional and cognitive states, it offers tailored support to improve academic outcomes and reduce dropout rates.

- **Self-Aware AI**: though theoretical, Self-Aware AI represents a future where AI possesses consciousness and self-awareness. Such AI could revolutionise engagement, grades, and pass rates by autonomously adapting to meet student needs. Its ability to evolve and respond to complex student challenges could offer highly personalised and transformative educational support.

The following section outlines AI's possibilities to enhance learning, as such sophisticated functions can enhance peer-based education.

2.7.3 AI in Facilitating Effective Learning

Effective learning hinges on three interactive aspects (Andersen, 2023; Kurni et al., 2023). First, like a human conversation, frequent and active engagement keeps students interested in complex material (Bork, 1999). Quality interactions, particularly interactive units, are vital in identifying learning issues (Bork, 1999). A promising format for computers in learning involves Socratic questioning with student responses (Gregorcic & Pendrill, 2023).

Long-range memory is the second necessary aspect. Computers can keep detailed student records like human tutors to inform future material presentation decisions. These globally accessible records can adapt to students' mobility (Bork, 1999).

The third aspect concerns the interaction language (Lynch et al., 2023). Countries should choose an effective learning language (Bork, 1999). New models of learning can lead to learning structures that are continuous, self-paced and mastery-based (Nnamani, 2023). Bork (1999), the mastery learning concept underpins such systems. It makes grades obsolete as learners master everything (Tuomi, 2023). Regular mastery checks and alternative sequences aid students who are yet to understand the material (Cai et al., 2023). Evidence is necessary to assess the effectiveness and best design of flexible AI learning systems versus traditional methods (Fredrickson, 2023). Despite the COVID-19 pandemic spurring eLearning adoption, researchers are scanning for potential benefits of AI-blended eLearning opportunities (Li et al., 2021). Resistance to change and job security fears might explain traditional universities' reluctance to implement blended learning approaches (Nam, 2019). Educators well-versed in conventional teaching approaches might find it challenging to adjust to new AI strategies (Rapanta et al., 2021). This practical learning discussion assumes that artificial intelligence and artificial consciousness are not equivalent—that is, intelligence is not equal to artificial consciousness (Haikonen, 2020). Table 2-7 illustrates the differences between AI and consciousness. Although the ability to experience, perceive, feel, reason, think, and understand often go hand in hand with humans and other advanced organisms, this need not be the case (Hasan & Hasan, 2023). Intelligence is about using logic and learning to act—learning from one's activities and those of other autonomous beings to foresee better and plan.

Table 2-7 Differences between AI and Consciousness

Difference between AI and Consciousness		
Category	**Artificial Intelligence**	**Consciousness**
Definition	It focuses on logic, learning, and action (Ng & Leung, 2020).	It concerns states of existence and experiences (Blackshaw, 2023).
Objective	Act, plan, and foresee based on data.	Unclear, often oriented toward experiencing states.
Key Aspects	We are learning from individual and collective activities.	Sensory experiences like sight and hearing.
Relation to Humanity	The purpose may conflict with long-term human welfare. AI is our brain-assisting device. It does not understand the consequences (Dehaene et al., 2021)	There is no inherent conflict, but the potential exists (Dehaene et al., 2021).
Self-awareness	It is not necessary for the function (Blackshaw, 2023).	It is an aspect but optional for its definition (Blackshaw, 2023).
Current State of Development	Advanced, with recent considerable progress (Weber-Guskar, 2021).	The objective is all that matters (Searle, 1998).
Public Perception	Shift from esoteric interest to widespread concern	It is still a theoretical, less immediate concern.
Ultimate Engineering Goal	Artificial General Intelligence (AGI) (Voss & Jovanovic, 2023).	It needs to be clearly defined.
Influence on Human Expansion	It sought to emulate the intellect that allowed human global spread.	It is not related to human expansion goals.

Contrarily, consciousness is about states of existence, such as seeing a cloudless sky, hearing birds chirp, sensing pain, and experiencing love (Dehaene et al., 2021). What an AI feels when allowed to run wild makes no difference and is “morally irrelevant” (Blackshaw, 2023: Abstract). All that counts is that it may have a purpose inconsistent with humanity's long-term welfare (Haikonen, 2020). It makes a minor difference whether the AI is aware of what it is attempting to do or what is known as self-awareness in humans (Ott, 2023). The fact that it pursues its objective "mindlessly" is all that matters (Blackshaw, 2023).

To give robots the extremely flexible intellect that allowed homo sapiens to spread out and eventually inhabit the world is the holy grail sought by computer engineers (Friend, 2018). Artificial general intelligence, or AGI, is what this is (Friend, 2018). Experts often characterise AGI as a distant goal (Voss & Jovanovic, 2023). In the past year, tremendous advancements in artificial intelligence have surprised everyone, including specialists (Daniel, 2024). With the advent of sophisticated conversational software applications, frequently referred to as chatbots, the debate over artificial general intelligence (AGI) shifted from an obscure topic among science-fiction enthusiasts and Silicon Valley to one that conveyed a sense of widespread public unease about an existential threat to our way of life and our environment (Federspiel et al., 2023).

2.7.4 AI and Adaptive Learning

The theoretical evaluation examines the existing theoretical frameworks and concepts related to peer-to-peer support, student engagement, artificial intelligence, adaptive artificial intelligence, and adaptive learning, as shown in Figure 2-9 (Yang et al., 2013). The enormously promising field of adaptive learning sees educators worldwide using adaptive tools to transform their practice (Hafeez, 2021). A single method, however, is unlikely to guide a student's complete education (Plass & Pawar, 2020). Moreover, we may not want such comprehensive guidance, as teaching hinges on building student agency, fostering decision-making, nurturing lifelong learners, and developing metacognitive skills. Learning and teaching play a pivotal role in honing students' ability to collaborate with others, including lecturers who ignite their interests and peers with whom they work, learn, and teach (McKay & Sridharan, 2024). Learning is a social experience that moulds individuals into mature social actors capable of engaging in civic society and leading productive lives (Pentury et al., 2023).

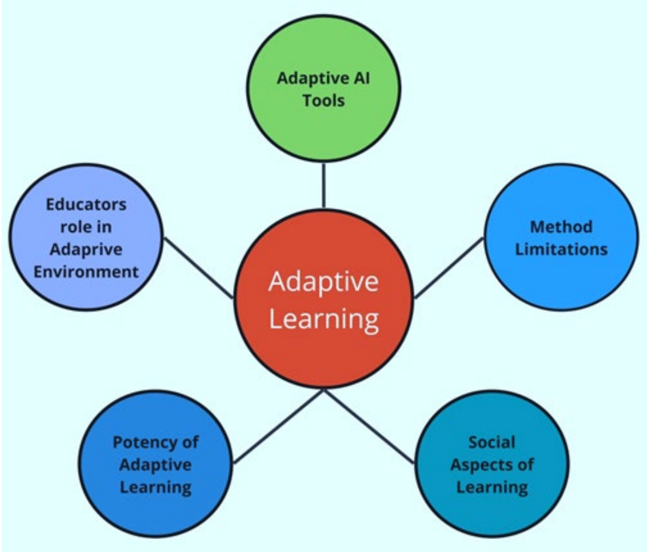

Figure 2-9 Theoretical Evaluation of Adaptive Learning and its Role in Learning and Teaching (Yang et al., 2018)

Figure 2-9 outlines the key components and perspectives surrounding adaptive learning:

- Adaptive AI Tools: These technological mobile means make sustainable interventions in educational practices by individualising applications for learning environments, tracking learning progress, and changing methodologies.
- Educator's Role in Adaptive Environment: Lecturers are always leaders and tutors who explain and don't explain to shape students' attitudes and help them to find their call and talents, the realisation of knowledge flexible.
- Method Limitations: Recognises the potential limitations of adaptive learning techniques, pointing out that while such methods can offer recommendations regarding education, they are not able to wholly dictate the learning process without employing human input; this is due to the value of student agency and metacognition skills.
- The potency of adaptive learning: The application of adaptive systems provides the opportunity to achieve rapid knowledge and skills training. All learners get content that suits them depending on the rate and style at which they can acquire knowledge. Such systems make learning individualised so that the learner receives content at his level of comprehension and at a time they can understand. Because of this, they can address learning needs and disabilities and increase the effectiveness of knowledge and skill training.
- Social Aspects of Learning: Adaptive learning promotes collaboration between lecturers and students or students alone, sparks interests, and enhances relatively mature social elements; more importantly, it stresses the community and the interactive

character of the entire learning process.

Figure 2-9 presents a multi-dimensional view of adaptive learning, integrating technology, educator roles, student engagement, and this educational approach's inherent limitations and potential (Capuano & Caballé, 2020). Adaptive learning is still a potent force for enhancing effectiveness (McDonnell & Crivac, 2023). Additionally, this technology can speed up our understanding of the most effective learning experiences for various students in diverse circumstances (McDonnell & Crivac, 2023). Instructors can adapt to a reality where they help all students discover their passions and achieve their maximum potential (Doyle, 2023). AI may adapt its feedback, necessary for peer-to-peer support, to content for students in response to their actions (Hu et al., 2023).

2.8 Artificial Intelligence

The development of modern computing owes much to the contributions of Alan Turing, who showed the feasibility of a universal calculator, known as the Turing machine, in 1936 (Turing, 1936). Turing's work laid the foundation for the construction of practical digital computers, as Ara Shaikh et al. (2022) informed, which later paved the way for the advancement of AI.

In 1950, Turing designed an experiment to evaluate a machine's intelligence, which became a benchmark for measuring computer intelligence (Benko & Lányi, 2009). Andresen (2002) shows that the father of AI, John McCarthy, 1957, developed LISP, a functional programming language specifically designed for AI (McCarthy, 1978).

Between 1965 and 1970, there was a lack of progress in AI, known as the "dark period," due to unrealistic expectations and simplistic approaches to designing intelligent machines (McCalla, 2023).

From 1970 to 1975, AI gained momentum, especially in disease diagnosis, and laid the foundation for present-day AI. Interest in AI's potential expanded to other scientific disciplines from 1975 to 1980 (Gabriel & McCarthy, 1984).

John McCarthy and Marvin Minsky played significant roles in AI development (McCarthy, 1978; Minsky, 1974). McCarthy focused on mathematical aspects of thought processes, while Minsky developed a machine to simulate nerve net learning. Both believed that AI should not replace human educators but enhance their capabilities (Chan & Tsi, 2023).

Herbert Simon proposed that humans have limitations in rational decision-making and emphasised the importance of developing tools to model human behaviour (Simon, 1984). Simon's work revolutionised information sciences and paved the way for computer simulations of multifaceted systems (Kamalov & Gurrib, 2023).

Donald Bitzer significantly contributed to computer-based learning and teaching through Project PLATO, which enhanced computer-based instruction and student autonomy (Cope & Kalantzis, 2023). PLATO systems showed the potential of computers in supplying high-quality learning and teaching and facilitating inquiry and thinking skills (Bitzer et al., 1967).

Alfred E. Bork explored the use of computers in learning and teaching and advocated for individualised mastery learning (Bork, 2002). He emphasised the importance of frequent and interactive interactions, long-range memory, and effective language of interaction in learning Bork (1999): The Future of Learning: An Interview with Alfred Bork, 1999.

Prevailing learning models assume that learning is a process of information transfer from teacher to student (Lebedyk & Strelnikov, 2023). Learning evaluation relies on memory recall, often using ineffective methods such as multiple-choice tests (Zhao et al., 2023). The models must consider students who do not learn or only learn partially through this information-transfer method, thus overlooking high-level skills like problem-solving (McDonnell & Crivac, 2023). This model of memory recall to improve retention is inadequate for the future, and alternatives need to be explored (Bork, 1999).

In online higher learning and teaching, evaluations focusing specifically on objectives, effects, and findings associated with using adaptive interactive AI-peer platforms are limited (Crompton & Burke, 2023). From an analysis of 138 studies globally, there is a notable shift in the geographic focus of research from the United States towards China (Crompton & Burke, 2023). Interestingly, learning and teaching departments have appeared as the most common institutional affiliation in these studies, suggesting a shift from past concerns about a lack of leadership from learning and teaching professors.

The principal area of exploration within these studies pertains to undergraduate students, accounting for 72% of the conducted research. Language learning dominates the subject area, covering writing, reading, and vocabulary acquisition. Of the intended beneficiaries of AIEd, 72% of the studies focus on students, 17% on lecturers, and 11% on administrators.

The deployment of an Explainable AI (XAI) in higher learning and teaching in 2022 enabled students to understand its actions and underlying rationale through collaborative experimentation. Remarkably, students successfully learned, although metacognition was supported with the help of the XAI system mainly by conversing with them (Arnold et al., 2022). Understanding the usage and impact of AI algorithms remains an area ripe for exploration. The relationship between the usage and the effects of AI algorithms still needs to be better explained. Current-day AI techniques are still traditional; however, other complex technologies like sequencing algorithms and immersive learning are available.

The potential impacts of applying AI in education are vast, with the prospect of increasing the student's academic performance and the level of activity on digital platforms. Nonetheless, it is necessary to thoroughly learn more about its impact on teaching and learning(Ouyang et al., 2022). This research study will continue to reveal the broader implications and augment the implementation of AI in learning environments.

Machine Learning (ML) has contributed notably in the last few years to arrive at solutions in any field, including higher education, to improve information on the quality of education, as stated by Rowe et al. (2022). For specific reference, institutions have emphasised retention, where machine learning methodologies highlight to estimate retention and causes of dropping out (Fahd et al., 2021). However, the endeavour of defining adaptive learning as a means of enhancing retention rates does not adequately succeed in the social context of learning due to the ongoing evolution of the concept. Adaptive systems, contrary to their classifications and, as already proposed, suffer from the "black box" problem made worse by proprietary software (Pugliese, 2016). As much as valuable adaptive tools exist, others can be deceiving or useless (Essa, 2016). It is, therefore, necessary to understand the current AI landscape.

2.9 Peer-to-Peer Support and AI

This general acknowledgement is that peer tutoring facilitates students' academic achievement, but the outcomes vary (Arco-Tirado et al., 2020). Below are questions related to the lesson: Does peer-assisted learning enhance academic achievement (Williams & Reddy, 2016)? Through peer tutoring, students perform better, as indicated in the literature, despite other works illustrating some levels of improvement in students' achievement (Greenwood, 2019). Shiner (1999 p.555) suggests considering the definition of "*peerness*" and the goals of interventions. The study explores AI's role in promoting peer engagement and development through text-based, online discussions focusing on emotional wellness (Alessandro et al., 2021). It also examines the dynamics of human-AI collaboration and the potential for feedback-driven AI to support academic success in complex contexts (Checco et al., 2021). The analysis highlights the difference between peer development and peer delivery, asserting a necessary fit among setting, strategy, and student (Shiner, 1999). According to Shiner (1999, p.564), peerness is seen as an interactive and participative intervention, "sharing affinity and experiences between them". Peer development is a form of collaborative learning where peer students learn by assessing others' work (Green, 2001). The inconsistency in findings may be attributable to the absence of rigorous evaluation tools or the heavy reliance on qualitative research designs, thereby complicating the conclusively linking participation in these programs with academic success (Greenwood, 2019). Regularly seen limitations in these studies include small sample sizes and variations between comparison groups. These observations underscore the need to explore alternative instructional strategies, a focal point of the present research (Greenwood, 2019).

It is, therefore, logical to turn to students' use of increased peer-to-peer support in connection with the discovery of their academic success pattern generally (Maheady, 1998; Balilah et al., 2020; Sharma et al., 2023). The relationship between the two areas is that if students' beliefs about their abilities and the value of the work are aligned, these beliefs potentially affect students' use of peer-to-peer support programs, including AI apps like ChatGPT and academic accomplishment (Rathore, 2023). They affect students' disposition towards designing and performing the peer-support system, including their accomplishments.

Common concerns with peer-to-peer support mechanisms also apply to AI and adaptive AI-peer-to-peer support platforms similar to conventional ones, as indicated in Table 2-8. Some of these challenges include the possibility that an AI algorithm might have some biases that affect its functioning; some facilities may not have adequate technology to support an AI; another challenge is maintaining the quality and effectiveness of support given. It is, therefore, imperative to address these factors to maximise the value of AI-based peer-to-peer support augmented by artificial intelligence.

Table 2-8 Problems Associated with Peer-to-Peer Support and Adaptive Programs

Problem	Description
Lack of Expertise	Due to this, peers cannot adequately help out or tutor in applying AI and adaptive AI. It can result in wrong information or advice propagation, especially when supplementing peer-support programs. Altogether, it remains necessary to guarantee that peers are appropriately trained and supplied with sufficient tools so that adopting such progressive methods does not contribute to these issues.

Problem	Description
Prejudice	Other colleagues may have some inherent belief or bias towards themselves in building AI and incorporating adaptive AI guidance. From such ignorance, prejudice and stigma might be imposed that may exclude deserving candidates; the problem of unfair treatment and unequal learning conditions can escalate—addressing these prejudices using practical assistance and training initiatives to reduce the occurrences of such notions and manage to rely on accurate, productive, and unbiased colleagueship within the AI-enhanced teaching study environments.
Lack of readiness	Peers can be unwilling or unable to help or tutor in subjects connected with AI and adaptive AI – this forms the basis of determining the availability of such help. This drawback can limit the effectiveness of peer-to-peer support programs among students and the main benefits they can derive from AI-integrated learning settings. Sufficient articles, journals, books, computers, and other vital requisites must be available for the peer tutor to engage students.
Absence of Diversity	While peers may also influence students' choices and bring diverse experiences, peers with limited diverse backgrounds may only introduce limited options for students to consider. The absence of diversification in such extremes can limit the possibilities of the learning progression and, therefore, may hinder other students from grasping the advantages of different perspectives. The institutions' implementation of diversity within peer-to-peer support programs is fundamental in improving the program's environment and the learner's overall education.
Inadequate feedback	While peers can offer suggestions, they may not be able to provide the feedback received from tutors or lecturers and may thus offer compromised feedback. Inadequate feedback can impact the success of peer-tutoring programmes, leaving some students with inferior guidelines to follow. To this end, the capacity of peer tutors should be supported and strengthened by providing faculty members with adequate training and tools defining professional supervision and assistance mechanisms.
Privacy and Ethical Concerns	In peer tutoring and support that involve students, the exchange of information that is personal to other students may bring about privacy-related issues. Such sharing of personal information may result in accidental violation of students' privacy and information – thereby infringing their privacy rights. Cohort support programs should be understandable to guarantee that the personal information provided by students will not leak while recognising that most programs are proper and reliable.
Need of Technology	Teaching and learning through peer tutoring and support in AI and adaptive AI could be substantially reliant on technological support, which means that learners who may not have access to the required gadgets may be disadvantaged. This support is because the use of technology in teaching and learning can help enhance the delivery of educational services. After all, the use of technology increases the channels of delivering educational services while at the same time inhibiting some students from fully accessing educational services because the available technology could foster inequalities. To this, an adequate supply of technological equipment in the classroom and other assistance to students who may not be privileged to own any necessary devices.

Various issues can affect the possibility of peer-to-peer support within learning and teaching AI and adaptive AI. Firstly, the question of peers' inability to support and tutor one another is quite striking. This inability is actual, given that the amount of information provided allows misleading recommendations or advice that may not be beneficial. Secondly, this considers the presence of prejudice among peers, even though this may be subconscious. If not addressed, they might mean that the current inequalities and stereotypes will continue in the AI learning and teaching environments.

However, peers' availability and readiness to assist in AI and adaptive AI must not be compromised, and they are needed aspects of peer support. Yet, this constant availability may push for limitations on access to this handy learning tool. Another complicated challenge that one has to face is the absence of variation in peers. The lack of diverse backgrounds in peer networks will likely limit the opportunity to learn from anyone other than their classmates. Also, peers may be unable to provide extensive feedback compared to professional tutors or lecturers, limiting the richness of the input. Sharing information, ideas and even emotions between students when they are tutoring peers brings out a lot of ethical and privacy issues.

The research aims to identify AI's function in fostering peer interaction and growth to provide emotional support within text-based, online, and peer-to-peer conversations. New leaders cannot afford to be empathy-challenged (Sharma *et al.*, 2023). It discusses how feedback–driven AI could work for one's academic success within such environments while emphasising the ability of AI to generate better quality and varied forms of peer interaction, from indications found in the work of (Yang et al., 2020). The development of the reciprocal peer technique underpins this process.

2.9.1 Peer-to-Peer Development

The Reciprocal Peer Teaching technique requires the student to alternate between the teacher and the learner (Bengesai et al., 2023). This shuffling has the following advantages: First, as stated by Lomas & Nicholls (2005), it enhances the learners' performance. In their research, Baidoo-Anu & Owusu Ansah (2023) posited that group responses fare much better regarding correct answers than individual responses; teaching also aids learning. Bowman-Perrott et al. (2023) have also completed research on many teaching methods and have found that reciprocal teaching is highly effective. However, these systems are often closely connected to particular subjects and can be more challenging to change.

When comparing peer-to-peer learning with AI, its ability to serve diverse educational requirements becomes evident (Checco et al., 2021). It is pivotal to have a basic outline of prominent theories as they indicate how further advancements will be made and create the groundwork for practical analysis of the consequent application (Topping & Ehly, 1998). These theories offer a guide for using AI to improve the effectiveness of peer-to-peer support interactions over the learning process, aiming at providing an appropriate personalised learning environment (Maheady, 1998). Therefore, using AI fused with conventional educational theories means we gain insight into improving peer-to-peer support and learning outcomes (Greenwood, 2019). However, peer-to-peer support has challenges, particularly in personalising the support.

2.9.2 Peer-to-Peer Individualism

The idea focuses on individualising the education process by considering the learner's peculiarities (Alam & Mohanty, 2023). The first advantage of the proposed adaptive AI is that it can change the steps taken based on engagement with the environment or people (Plass & Pawar, 2020). Indeed, this capability of AI lets it adjust the topics and how a learner is taught depending on the learner's habits or progress, enhancing learning. Reactive AI is one of the classifications of AI in which machines can adapt and modify themselves following the interaction in their surroundings or with users. This capability allows AI systems to function based on the client's preferences and requirements, enhancing the effectiveness of the interventions. Adaptive AI is flexible to fit a particular need through such a mode of interaction since it has broader applicability in many fields, such as education involving peer learning (Gupta, 2022; Kabudi et al., 2021).

Because of the challenges of artificial intelligence, there is a rising preoccupation with more and more standardisation of the technical part of the adaptive AI (Wang et al., 2021). The lack of clear guidelines hampers the creation of programs that can be easily integrated into the existing environment besides tackling ethical issues (Wang et al., 2021). Also, it is not still clear whether adopting personalised AI affects learning outcomes (Wang et al., 2021). Despite emerging research exhibiting that personalised learning can improve knowledge gain Jose (2021) & Holmes et al. (2023), more studies are necessary to establish and understand the optimal way of introducing adaptive AI in the learning process. It is possible to determine how personalisable AI affects students' interest, motivation, and outcomes in terms of acquiring knowledge for the long term (Rizkallah & Seitz, 2017; Çakir, 2019).

This idea made developing conversational AI and natural language processing, two needed components of personalised AI, possible (Salman, 2013).

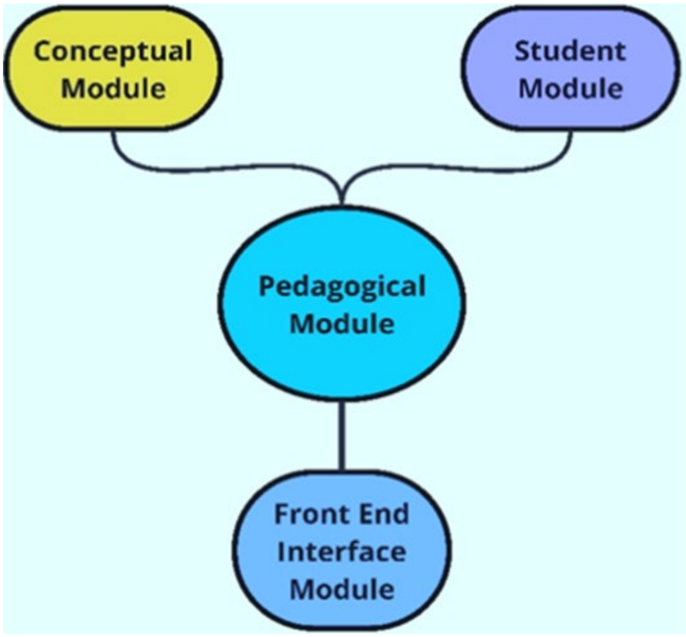

Figure 2-10 Architecture of Intelligent Tutoring System (ITS) (Salman, 2013)

The literature review synthesises the pioneering endeavours concerning personalisable artificial intelligence, which Donald Bitzer spearheaded. Bitzer and a group of computer scientists began advancing the PLATO system at the University of Illinois at Urbana-Champaign during the early 1960s. Salman (2013), illustrated in Figure 2-10, shows that incorporating the conceptual model within a system signifies individual problem-solving capabilities. The student module provides a structure for recognising a student's existing degree of comprehension in a particular field of study. The pedagogical module or tutoring strategy receives feedback from the dominion and student modes and generates instructional strategies and corresponding actions. The front-end interface of an Intelligent Tutoring System (ITS) is a crucial integration point for various forms of information that enable effective student interaction. These may include graphics, text, multimedia, keyboard, and mouse-driven menus.

Joseph Weizenbaum was another computer scientist who significantly contributed to developing personalisable AI (Stilgoe, 2023). In the mid-1960s, Weizenbaum developed a natural language processing program called ELIZA. ELIZA could speak with a user based on their input, and ELIZA intended to mimic a psychotherapist. ELIZA was one of the first chatbots and has significantly expanded natural language processing and conversational AI. Weizenbaum's work on ELIZA helped advance the field significantly and laid the foundation for modern-day chatbots' intelligent, personalisable AI assistants, prompting further AI peer-to-peer support discussions.

2.9.3 Peer-to-Peer and AI

Learning and teaching are undergoing significant transformations Carter and Kennedy (2006), particularly in the medical and educational fields (Heleta & Chasi, 2023; Rowe et al., 2022). These transformations are motivated by diverse influences embracing the needs of students and management. There is a need for alternative classroom procedures (Greenwood, 2019). Despite technology integration, the conventional approach to learning in general undergraduate education, which involves a teacher standing before students and reading textual material, followed by written exams that equally assess all classroom areas, needs to be updated (Ellis et al., 2009; Kanyane, 2023). Current learning trends are converging towards interactive, student-centred, and tailored learning models that offer closer engagement, collaboration, improved conception, and a broader scope of learning conclusions for each student or group (Sointu et al., 2023). One significant learning method shift recently gained prominence is the flipped classroom, which positively affects learning practices[6] and may assist AI peer-to-peer support programs.

There are advantages to involving students in peer teaching opportunities, including improved learning outcomes. Firstly, groups tend to perform better than individuals in answering questions correctly. Secondly, the act of teaching itself promotes learning. Thirdly, peers can present information in a more easily understood and relatable manner, particularly in cross-generational communication. Reciprocal peer teaching with AI is a practical approach to enhancing student engagement and helping students learn (Prideaux, 2003), illustrated in Figure 2-11. In the annals of tutoring systems (ITSs), the protracted and onerous development process has been a longstanding obstacle (Sottilare, 2011). Status equals or matched

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6 According to the Academic Assessment of Higher Education (HE), students' performance over the past twenty years has been ineffective despite recent improvements (OECD Indicators, 2018). Reports from international bodies such as the (Commission, 2014), OECD Indicators (2018) and Vossensteyn et al. (2015) indicate that Graduation Rates (GR) fluctuate significantly from country to country, ranging from 18% to 77% OECD Indicators (2018), while Dropout Rates (DR) range from 7% to 48%. In Spain, official data from the Sistema Integrado de Información Universitaria (2017) shows a low GR of 33.2%, a high DR of 35.2%, and a Change of Studies Rate of 12.3%. First-year students are primarily affected, with a DR of 22.5% and a Change of Studies Rate of 8% in the first year.Dwindling degrees of student retention and poor academic results have a significant mental impact on young people and their extended families and substantial societal and financial implications. For instance, in Spain, these costs have been estimated to be close to 0.3% of the national Gross Domestic Product (Peña, 2010). Institutions have addressed these problems and improved the efficacy of higher education (HE) by implementing various procedures, guidelines, and training programs. These include political measures such as changes in organisation and financial motivations, organisational measures such as the implementation of student success programs, and classroom measures such as the use of student-centred activities and experiential learning (Brint & Clotfelter, 2016; Goldrick-Rab, 2010; Kuh et al., 2006; Vossensteyn et al., 2015).

companions engage in peer tutoring to help each other gain knowledge and skills (Arco-Tirado et al., 2020). This method has extensively supported new students' peer tutoring programs, as shown in Figure 2-12. Institutions have increasingly adopted student success programs to improve student outcomes, investing significant resources in new student adjustment programs. These programs aim to help new students integrate into their academic and social environments through different approaches, including learning communities, peer-to-peer support, and tutoring.

Figure 2-11 Peer-assisted learning Methods adapted (Prideaux, 2003)

These systems often exhibit a solid connection to the subject matter and resist adaptability (Heleta & Chasi, 2023).

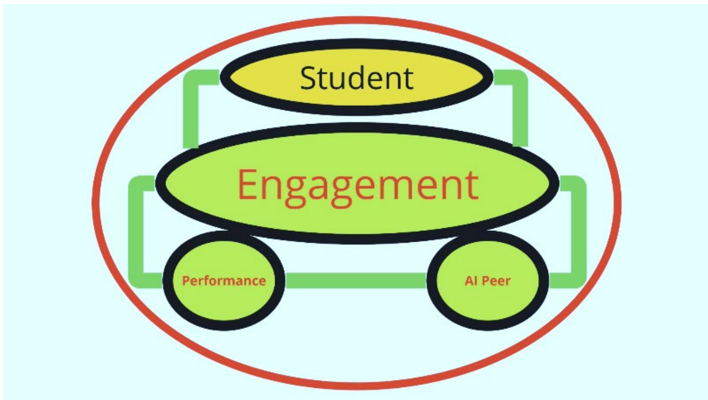

Figure 2-12 Adapted Peer Tutoring Program (Arco-Tirado et al., 2020)

Topping (2023) has shown that the effectiveness of peer tutoring has been widely studied, with results varying. While studies of peer support have demonstrated positive effects on students' academic success, others have found little to no impact (Carter & Kennedy, 2006). One likely reason for this variability is that programs need evaluation measures or use qualitative research designs that make it challenging to find connecting affiliations between involvement in these programs and academic success (Ellis, Marsh, and Craven, 2009). Limitations in scientific evidence quality often arise due to small sample sizes and disparities between comparison groups. The need for alternative classroom procedures is found in the study (Greenwood, 2019).

The Peer-Tutoring Program (PTP) is a multi-year, secure-role, dyadic peer-tutoring intervention. Its primary aim is to enhance students' self-regulated learning skills, focusing on subject-specific content. The program aims to enhance student's overall intellectual achievements by improving their academic and social adaptation to the university experience. It draws inspiration from counselling approaches (Arco-Tirado et al., 2020), as the adapted Figure 2-12 shows. Significant literature is available on increasing student engagement through PTP and group assessment (Farr-Wharton et al., 2017; Holmes, 2023). The possibilities include effective and participating learning approaches like self and peer involvement (Tight, 2019) to present programmes to at-risk students. Price and Tovar (2014) identified four impact practices affecting PTP engagement, illustrated in Table 2-9.

Table 2-9 Impact Practices (Price & Tovar, 2014)

Impact Practices
Students are working in groups on tutorials.
Group engagement is separate from formal sessions, specifically on assignments.
Opportunities exist for AI in peer tutoring.
Discussion of concepts by adding readings from instructors.

Group tutorials encourage collaboration and introduce participants to various perspectives, strengthening participants' thinking skills and catalysing increased student involvement(McKay & Sridharan, 2024). Like this, informal group projects outside formal classroom settings foster a sense of ownership and heighten engagement through collaborative problem-solving (McKay & Sridharan, 2024). By creating a reciprocal learning environment where students serve as both educators and learners, peer tutoring opportunities further enhance this engagement and help students gain a deeper understanding of the subject (Oni & Viswanathan, 2016). Additionally, discussions with lecturers about supplemental readings offer ways for students to expand their knowledge beyond what is covered in the core curriculum, raising student involvement (Devi, 2023). These methods work synergistically to create a vibrant and thriving learning ecosystem.

Due to the time constraints of academics, implementing these propositions is restricted (Ossiannilsson, 2018). For this reason, adaptive AI peer-to-peer support platforms are worthy of consideration as they potentially offer elements of peer-to-peer interactions. Illustrated in Figure 2-13 are the pivotal aspects of peer-to-peer support and tutoring.

Figure 2-13 Elements of Peer Interaction (Nel et al., 2023)

For the reasons mentioned, three main factors, exploration, enablement, and infusion, play a significant role in AI peer-to-peer tutoring, as posited by (Nel et al., 2023). This role is vital because exploration discovers the areas where learners lack understanding, allowing for relevant interventions. Implemented in this way, it helps make the system more responsive to the needs of the tutors and more engaging to the students. The second consideration is enablement, which facilitates the learning process management from the student’s side. Doing so gives them the necessary knowledge and self-esteem to face academic tasks and overcome them independently. Lastly, infusion involves embedding subject matter within broader contextual frameworks. This integration enhances comprehension, application, and long-term retention of knowledge. Exploration, enablement, and infusion work together, amplifying the effectiveness and impact of AI peer-to-peer tutoring initiatives (Nel et al., 2023).

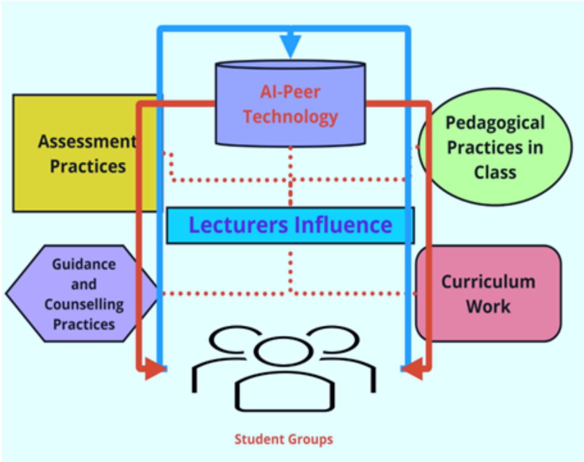

Figure 2-14 Adapted dimensions of the Flipped Classroom module (Sointu et al., 2023)

Thus, dependence on technological advancement in learning and teaching AI proctors for peer help may be a limitation as much as the student lacks the appropriate devices. All these complex problems, therefore, require a systematic research approach. To remedy this, increased cultivation of different means of learning and teaching, such as flipped classrooms, should be accomplished more effectively by artificial intelligence (Brewer & Movahedazarhouligh, 2019).

Figure 2-14 displays the components of a flipped classroom model coherent with the principles of personalised learning and teaching. The flipped classroom model focuses on active student engagement and intends to enhance classroom time. However, this approach is traditionally adopted in the physical disciplines (Ozdamli, 2016). Sein-Echaluce et al. (2019) literature on flipped classroom learning emphasises that learning and teaching technology and instructional design help implement learning environments according to the student. The advantages of the recommended approach are higher final grades and lower attrition rates. Notably, technology is elemental in supporting the flipped classroom models; it includes feedback and analytical tools to assess time management and stakeholders' engagement (Huang et al., 2023).

Nevertheless, AI peer-to-peer support alone cannot overcome all the problems due to a lack of investment in fundamental professional support, infrastructure and exclusionist policies (Kasneci et al., 2023). In Mitchell's (2023) view, peer-to-peer support is underestimated and is still one of the most necessary elements of teaching goals. Therefore, to get a picture of contemporary students, their chances for success, and perspectives of dropping out, it is crucial to comprehend them in terms of several complex components at once (Fenton et al., 2023).

As we transition to the broader scope of artificial intelligence, these complex considerations become significant in shaping AI's role in learning, teaching, and peer-to-peer support interactions. AI's capacity for adaptability and personalisation aligns with the principles of tailored learning and teaching experiences, such as the flipped classroom model. By incorporating AI's strengths, lecturers can develop better ways to increase engaged educational settings and improve the usual usage of Learning management systems and innovative learning and teaching models.

2.10 Engagement and AI

Wang et al. (2021) & Tinto (2017) suggest student engagement[7] is the reciprocal interaction between institutions and students to refine the student experience, learning outcomes, and the institution's performance and reputation. It requires both parties to give time, endeavour, and resources. Kuh et al. (2008) define student engagement as educationally sound activities that yield quantifiable results inside and outside the classroom. Krause & Coates (2008, pp.495–503) define it as ″the extent to which students engage in activities linked with high-quality learning outcomes″. A further definition by Hu & Kuh (2002: 556–571) states that commitment is "the quality of effort students devote to educationally purposeful activities that contribute directly to desired outcomes"[8]. Is there a relationship between student engagement and performance? (Lee, 2014).

Lewis et al. (1992) asserted that effective teaching and learning environments are crucial for higher education to have a transformative impact on students' academic development. According to his research, students who engage in challenging coursework, collaborate with peers, and receive effective instructor feedback are more likely to succeed academically. Therefore, by developing student engagement, an institution can directly influence the margin

7 "The concept of student engagement stands for two key components. The first is the amount of time and effort students put into their studies and other activities that lead to the experiences and outcomes that constitute student success. The second is how higher education institutions allocate their human and other resources and organise learning opportunities and services to encourage students to participate in and benefit from such activities"(Tight, 2019: 691–699).

8 How College Affects Students: Results and Perspectives from Two Decades of Study Lewis et al. (1992), "the principle of engagement may seem straightforward and obvious: the additional time and effort students invest in their learnings, the to a greater extent of knowledge they acquire. Similarly, practising and receiving feedback on writing, analysing, or critical thinking skills improves ability. Such activities also cultivate a foundation of skills and attitudes vital for leading a fulfilling and productive life after graduation. In other words, students who actively take part in educationally valuable activities during university develop a mindset and disposition that expand their potential for ongoing learning and personal growth."

of learning and teaching quality. Pascarella & Terenzini's (1979) study emphasises the profound influence of university experiences on students' personal and social development. The research shows that higher education encourages self-awareness, self-assurance, and personal growth through exposure to diverse perspectives and experiences. Positive outcomes have been consistently linked to detailed sides of commitment: envelopment, time expended on task, and value of effort. (Lewis et al., 1992) highlight the importance of nurturing supportive learning environments with close student-faculty relationships and access to academic and individual support services that facilitate students' personal growth. Earlier studies have shown that participating in extracurricular activities positively correlates with improved outcomes (Eccles et al., 2003; Fredricks, 2012).

Academics are actively exploring methods to promote interaction among students in both large and small classes. They advocate for and sometimes mandate group study sessions while utilising feedback to foster student engagement. In addition, academics strive to motivate students to understand the subject matter rather than simply memorising details thoroughly. They connect their research with teaching to create a stimulating and captivating learning environment. Staff members support extramural events in the institution's broader campus community. It is indispensable to recognise that encouraging student engagement needs the involvement of faculty members.

Learning effectiveness refers to a dynamic process through which learners interact with formal and informal information, skills, and realities. As a learning and teaching process, education has the unique potency to change peoples' consciousness, behaviour, competencies, values, and choice patterns. Learning effectiveness can provide the highest quality of education while achieving the intended learning outcomes as prescribed by the intended learning standards. Thus, promoting students' growth entails fostering the processes that enable them to become knowledgeable and develop, affecting their thinking and feeling processes.

In expanding any new innovative technology, it is imperative to consider possible issues and concerns in their application, especially concerning one's students' beliefs, attitudes, and engaged state, as depicted in Table 2-10. The feeling of confusion and distrust of AI and adaptive AI by the students results in low engagement levels due to misunderstanding. Insecurity might arise from fear, like in K-12 or higher education, where teaching might be a profession under threat from artificial intelligence applications that perform or facilitate activities demanding intricate or innovative thought. Artificial intelligence experience is not free from harmful effects: frustration appears due to students' lack of control of the learning process.

Another potential drawback that may impede organisations' engagement is the decision-making opacity: it may contribute to biased perceptions by people and encourage their non-commitment. Lack of feedback on what the AI system is doing for the students can also cause the students to lose interest in learning. Potential issues are that learners might be uncomfortable using personal data to engage in various artificial intelligence technologies if their information is grossly misused. Also, reduced social interaction due to the implementation of AI may be a disadvantage to students who perform well in group-based settings.

Table 2-10 Challenges Associated with Student Perception

Challenges Related to Perceived Organisational Support, Attitude, and Participation in AI
Students should be aware of how AI and adaptive AI work; therefore, they will be confused about the technology. This lack of knowledge can bring about negative attitudes and perceptions towards AI, which keeps them off the platforms and systems.
Uncertainty about AI taking over human professors might create doubts and make students fail to focus or put effort into their classes. This issue may affect the education of lecturers and students involved in computer science, economics, engineering, arts, and social sciences, among others. It may include course material that requires analysis or innovative ideas.
It explains how students can become dissatisfied and disinterested when AI and adaptive AI are declarative about excluding the student from the learning process. Because of this dissatisfaction, these students feel they do not have agency over what they are and how much they are learning, especially when AI creates individual learning paths for students.
If AI and adaptive AI are not transparent with the students regarding decisions, such as the marking points they give, the students may feel that the technology is biased or even unfair. This bias is why students may develop this mistrust, which makes them have nothing to do with the learning process.
The students may lose interest and fail to study hard when they deem the AI and adaptive AI systems insufficient for making adequate comments on the student's progress and understanding of the content taught.
In the same way, the student may feel bored and remove effort in learning if they think that the AI or adaptive AI systems cannot give necessary feedback on their learning achievements or comprehension.
Privacy concerns: Some possible issues arising from AI and adaptive AI systems include: Students may be concerned about theft of their information and data privacy regarding particular problems, making them very cautious or even reluctant to use the technology in various areas.
Adaptive AI and plain AI may reduce social relations between students and lecturers and lessen learning motivation and involvement. This lack of involvement is primarily a drawback for social learners who actively participate in class and need social interaction and collaborative learning.

Based on Tinto's (1999) theory, an institution could apply some measures to help students become more active and participate in other activities that could lead to better student attitudes.

Engaging students to be actively involved in the university's happenings in terms of administration, club participation, or affiliations creates a sense of responsibility and partnership between the students, their institution and their fellows. It can result in improved attitudes toward the university experience.

Vayre & Vonthron (2016) conducted a study examining online student engagement and analysed two factors: social support and a sense of community. This study attributed online student engagement solely to teacher support. In the same year, Cai (2017) reflected on her experience with online learning and teaching training and proposed three strategies to promote student engagement: developing a vision for excellence, designing meaningful tasks, and fostering a sense of community. Cai suggests that setting up a community in an online course could enhance students' understanding of ownership and pride, leading to improved learning outcomes. Two other researchers, Stephan (2017) and Deschaine & Whale (2017), also support a learning community that enables students to engage with their peers and instructors actively; Gray & DiLoreto (2016) further reinforce this notion.

Price & Tovar (2014) suggested that high retention rates and degree completion hinge on empowering and motivating faculty to integrate practical, active, and collaborative learning practices, enhancing student engagement. Addressing institution-wide policies and procedures offers more support for students. Faculty is pivotal in creating a learning environment that promotes student achievement. The complexities, however, of online learning make it challenging for faculty to build a virtual setting that effectively engages students, as noted (Sher, 2009). Flynn (2014) emphasised the importance of engaging students for postsecondary student persistence and achievement.

Robinson & Hullinger (2008) said student engagement shows high-quality teaching, while Ahlfeldt * et al. (2005) emphasised the importance of engaging students in their learning. To keep students interested in their lessons, teachers must modify their approaches in response to shifting student needs and attention spans. However, determining student engagement in online courses can be challenging (Gray & DiLoreto, 2016). Researchers have used ways to measure student engagement, including aptitude, dynamic, participative, and accomplishment (Li & Xue, 2023). Academics apply diverse methods to measure student engagement, including aptitude, emotive, participative, and accomplishment. Young and Bruce (2011) developed an online community and engagement scale to measure unity with the instructor and classmates and engage with the learning. Lecturers must deliberate how to involve a distinct populace of students in an ever-changing environment of blended online edification.

In student-content interaction, there is an emphasis on individualised learning. Social constructivism suggests that students collaborate and interact with others to create knowledge, which they internalise to generate understanding. According to Seery et al. (2021), engagement with content should concentrate on interacting with it to enhance thinking and improve the student's performance. Emphasising the content or subject in collaboration among students and studying resources facilitates individualised learning.

According to Moore (1989), student-content interaction, by definition, is engaging with educational content and developing a deeper understanding, altering their perspective, or restructuring their cognitive frameworks. This form of interaction is considered fundamental in learning and teaching. Students must be given access to content for successful learning, with student-content engagement as the essential variable (Tuovinen, 2000; Zimmerman, 2012). Every student must meet the learning goals of a lesson presented upon login. Interacting with online learning involves various activities, such as navigating the Learning Management System (LMS), conducting required readings, and trying assignments. Moreover, students can interact with the content by viewing multimedia and accessing search engines such as Google Scholar or university libraries, as highlighted by (Banna et al., 2015).

Martin & Bolliger (2018) suggest that online instructors design original tasks that encourage students to examine projects from different viewpoints and use pertinent information astutely instead of simply supplying a list of resources. Real-world projects that promote thinking and foster student-content interaction should be the focus of online instruction. Instructors and instructional designers should avoid relying solely on text-based formats and incorporate various subject matter presentations, including audio and video, to motivate students to gain knowledge (Wiburg et al., 2017; Mucundanyi, 2021). Supplying multiple formats allows students to learn differently, given their diverse learning styles (Schilling, 2009). The content organisation should challenge students' thinking to gain the necessary knowledge for a course and serve as a resource for interaction with others.

The achievement of academic objectives established by instructors through analysing student learning data over a specified period is known as student learning effectiveness (Sun et al., 2017). Evaluation is crucial in assessing the success and continuous improvement of educational programs. Learning outcomes provide a shared understanding of the course or program goals for both lecturers and students. In e-learning, we have used specific design elements like cognitive, instructional, and social representation to assess learning efficacy.

These design features aim to cultivate and promote higher-level thinking skills through research and consideration.

The acknowledgement of the effectiveness of human tutors in adjusting instruction to overcome learning barriers like frustration or withdrawal during one-on-one tutoring sessions is widespread. Sensitivity to students' affective states, moods, and emotions significantly contributes to the success of human tutors. To achieve comparable effectiveness, computer-based Intelligent Tutoring Systems (ITS) must be able to "perceive" student change and enhance execution by deciding on instructional strategies, such as feedback. The current ITS, however, needs this ability. Recent research focuses on modelling the emotions of virtual characters rather than evaluating the student's" compelling state" (Sottilare, 2011).

Evaluating the effect of adaptive AI-peer-to-peer support platforms on retention and performance needs measuring student engagement (Seo et al., 2021). Engagement is linked to outcomes, making it necessary for assessments (Deneen & Hoo, 2023; Hagopian et al., 2001). Student assignation shows the level of involvement, significance, and commitment a student has towards their learning experience. Engaged students will participate in class, complete assignments, and perform better in their courses. Additionally, active students are expected to continue their enrolment and persist towards graduation, leading to higher retention rates.

The Tinto and Bean framework can provide insight into the connection between student engagement and retention. Tinto's model suggests that a combination of educational and social integration influences students' decisions to persist in their academic pursuits. Academic assimilation refers to students feeling a sense of belonging and support within their academic program. On the other hand, social integration is a student's perceived support by other students and other aspects of the university environment. The level of engagement a student has strongly determines the two factors. For instance, connected students will likely have relationships with peers and faculties, engage in co-curricular activities, and utilise service learning services. The activities discussed above increase one's level of participation in society, both in learning institutions and social settings.

Students use techniques such as questionnaires, interviews, or even direct observation of students' activities in class or online platforms and forums. By tracking the extent of engagement before introducing the adaptive AI-peer-to-peer support platform, scholars can assess the platform's influence on student engagement, retention and success rates. For instance, the students are more engaged or show more activity in class after operating the platform. In that case, the platform ensures interaction and enhances the learners' academic performance.

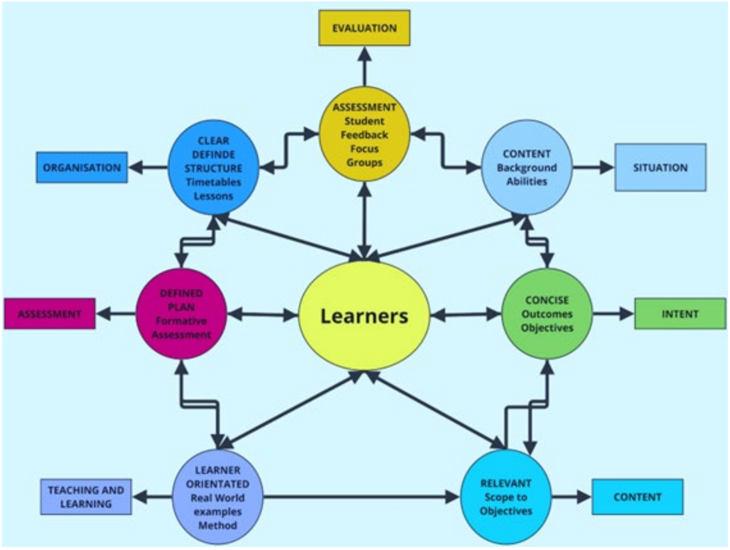

Figure 2-15 Adapted curriculum from A student's perspective (Sottilare et al., 2018).

Intelligent Tutoring Systems (ITS) provide personalised one-to-one instruction tailored to individual learning needs and progression towards educational objectives, as illustrated in Figure 2-15. The prospect of repurposing them for different domains is non-existent. The Generalised Intelligent Framework for Tutoring (GIFT), by Sottilare et al. (2018), offers promise. This open-source program goes beyond subject-specificity. It embodies adaptability and versatility. The GIFT framework is a breakthrough platform that empowers users to craft full-fledged tutors with bespoke content. Its domain-agnostic character circumvents the constraint of subject-specificity. It unlocks the potential for repurposing materials, thereby mitigating both the temporal and financial burdens that typically bedevil the development of tutoring systems, as shown in Figure 2-13.

In GIFT, evaluation functions concentrate on improving empirical skills, which hold relevance for adaptive instructional methods, intelligent tutoring systems (ITSs), and related technologies. The evaluation features a fundamental component of GIFT offering an invaluable testing ground, depicted in Figure 2-16, facilitating a comprehensive assessment of the impact of environmental factors, instruments, models, and methodologies on a diverse array of outcomes, ranging from engagement and learning to performance, retention, reasoning, and skill transfer.

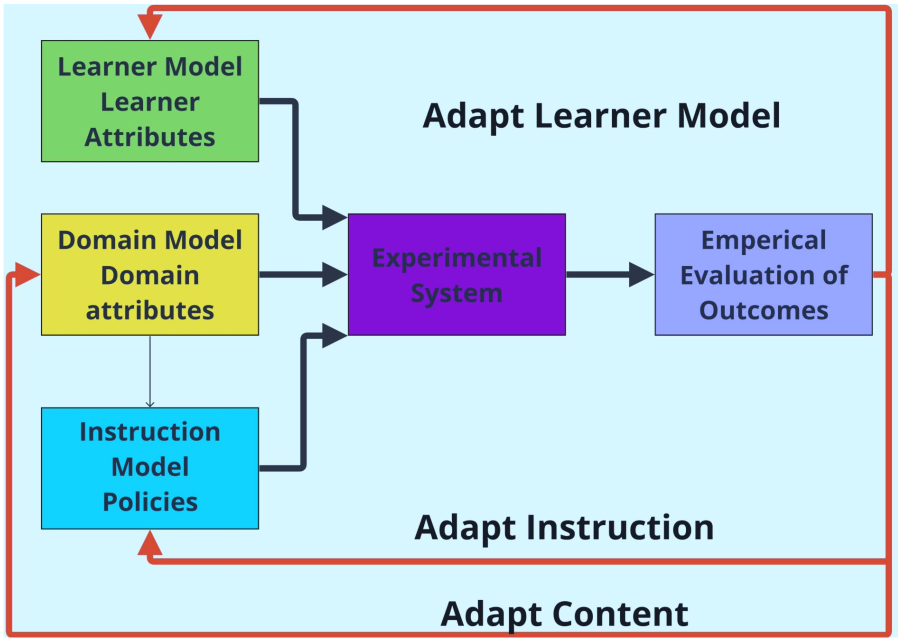

Figure 2-16 GIFT evaluation Testbed Methodology (Sottilare et al., 2018)

Students' perceptions of the tool's usefulness, user-friendliness, and alignment with learning and teaching objectives influence students' adoption of ALT. However, anxiety and computer self-efficacy can intervene and affect the use of e-learning systems. A decrease in computer self-efficacy can increase anxiety levels and hurt the apparent ease of use of an e-learning system. Students' attitudes, emotions, and indifferences towards learning tools can significantly influence their satisfaction with using an ALT tool. In general, learners perceive acquiring modern technology as enhancing their academic performance and equipping them for the future (Zogheib et al., 2015).

ALT may improve students' beliefs or attitudes towards learning more effectively than their academic performance (Mampadi et al., 2011; Yang et al., 2013). It is crucial to consider a student's frame of initiative when evaluating the findings of studies on the effectiveness of ALT. Students with higher levels of enterprise (better performers) may use the tool more often. In comparison, those with lower levels of creativity (poorer performers) use the device less often, which is synonymous with peer-to-peer support.

Exploring engagement as part of a student's belief system is vital in the search for a complete understanding of their cognitive processes (Beck et al., 2023). Examining student learning styles has recently received more attention (Midford et al., 2023). Research into students' feelings and beliefs has become an increasingly prominent study area (Beck et al., 2023). It is crucial to understand that students bring their unique personality traits into a language class

(Midford et al., 2023). These traits, which include their beliefs, views, and personal language preferences, can influence their learning journey (Impala et al., 2023).

Song (2022) says that the effectiveness of AI is contingent on the quality of curriculum development and the level of AI integration into the learning experience. It exposes the students to other learners, making them well-engaged. It increases the students' satisfaction, enhances their motivation for learning, and reduces the feeling of isolation.

To achieve the goal of generating targeted emotions and thoughts with students as proposed by Halverson & Graham (2019) in the Intelligent Learning Environments (ILEs) thus the self-regulated help, the beliefs and, therefore, achievement of the students are enhanced as highlighted by (Baidoo-Anu et al., 2023). Baidoo-Anu et al. (2023) echoed the significance of advocating for cultural understanding and variability to improve learning outcomes.

Additionally, providing feedback, supported learning, and suggestions provide a custom understanding to foster higher levels of student accomplishment (Boud & Dawson, 2023). These ILEs should be well-designed and properly implemented to ensure they are realistic and free from ethical compromise (Sottilare, 2018).

The growth of sophisticated AI technologies has spurred the evolution of Educational AI Tools (EAITs) (Choi & Levinthal, 2023). Choi & Levinthal (2023) show the design of EAIT tools to help instructors make informed decisions about their pedagogical practices. Even with the potential performance benefits, there has been limited integration of EAITs by lecturers, and the belief in such tools among educators still needs to be discovered (Choi & Levinthal, 2023). Tint's (1975) & Bean's (1988) theories align the importance of engagement with grades and pass rates as part of achievement.

2.11 Grades and Pass Rates and AI

Grades and pass rates as part of academic performance and achievement play a significant role in students' learning success, specifically in higher education (Jama et al., 2009).

With the emergence and growing prominence of AI and adaptive AI, it becomes increasingly important to explore the potential advantages and disadvantages of integrating these technologies to enhance academic performance (Guarda et al., 2023).

2.11.1 Competencies and Approaches

Studies conducted by Aitken (1982) & Higgerson (1985) and recently Stephen & Rockinson-Szapkiw (2022) have shown that the perceived quality of life and competencies significantly influence student persistence, grade and pass rates. Necessary competencies should be maintained and developed to support grade and pass rate improvement.

2.11.1.1 Competencies

Research into the efficacy of AI peer-to-peer support systems as antecedents to enhance academic success is imperative. In this context, the significance of Bloom's Taxonomy, as depicted in Figure 2-17 and Figure 2-18, reinforces the focal point of the study and its relevance to grades and pass rates.

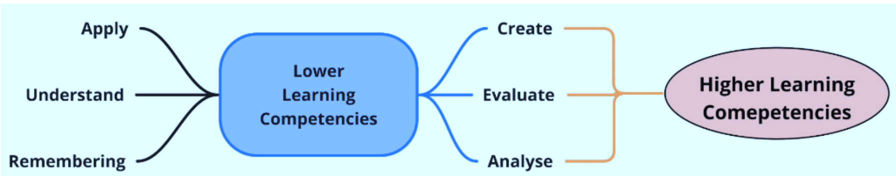

Figure 2-17 Lower and Higher Learning Competencies (Jose, 2021)

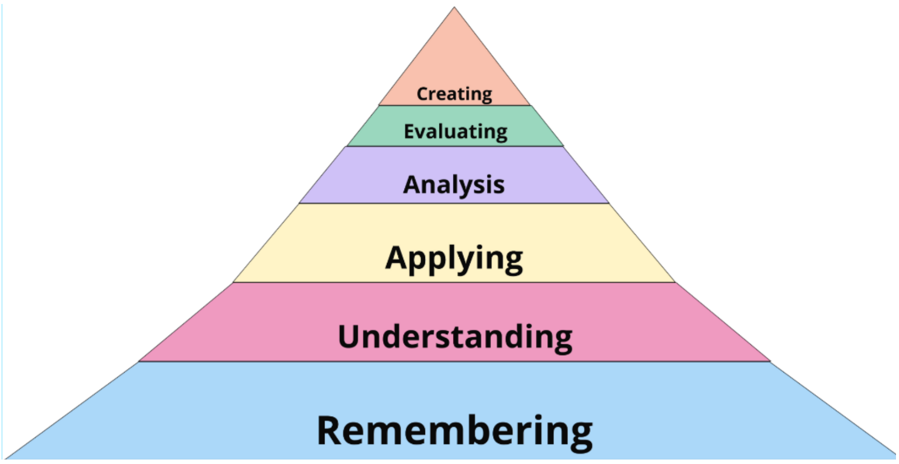

Figure 2-18 Bloom's Taxonomy Revised (Oliver & Dobele, 2007)

There are six levels of cognitive thinking, according to Bloom (1984), from simple remembering to the more complex creating stage, illustrated in Table 2-11.

Table 2-11 Adaptive Learning Technology Competencies (Bloom, 1984)

HIGHER LEARNING COMPETENCIES	LOWER LEARNING COMPETENCIES
Create	Apply
Evaluate	Understand
Analyse	Remember

Bloom's Taxonomy helps assess cognitive skills across various disciplines, including information technology. The taxonomy classifies degrees of cognitive learning, ranging from the lowest level of recalling information (knowledge) to the highest level of evaluating outcomes through comparison. Additionally, Bloom's Taxonomy is practical for retrospectively assessing the degree of a given task. It is a hierarchical framework that moves from simple to complex cognitive levels, making it an effective tool for teaching and learning. The classification advantages for lesson planning and checking include constructing the lessons, checking on assignment difficulties, determining the level of cognitive achievement, and adding thickness to lessons.

Earlier Figure 2-17 consists of two competencies: Lower-order learning, which pertains to improving and processing information, and high-order learning, which emphasises creativity and analytical thinking. The six cognitive levels, create, evaluate, analyse, apply, understand and remember, can help lecturers and students better understand the depth needed for a particular topic or assignment (Krathwohl, 2002; Gorgone et al., 2003; Athanassiou et al., 2003; Jose, 2021). The lower competencies deal with processing ideas from the environs, while the advanced competencies use the knowledge from the more insufficient competencies to create developed knowledge. Oliver and Dobele (2007) suggested that if first-year courses are too cognitively demanding, it may impede students with lower ability levels and prevent them from building a solid foundation (Adijaya et al., 2023).

Studies have shown that university performance influences students' resolve to complete their degrees (Bean, 1988). Student perseverance, resourcefulness and departure integrate the concept of solidarity in a broader sense, emphasising the importance of student integration (Jones, 2023). Incorporating multiple perspectives enhances our understanding of student persistence. Pascarella and Terenzini (1979) proposed that satisfaction is a precursor to performance, with students who are content with the university environment achieving improved scores on graded assessments Beelick, (1973), showing a positive correlation between satisfaction, grade score average, and university grades. Knox, Lindsay, and Kolb (1992) also saw that students with elevated university grades were likelier to perceive their courses as interesting, perform well, gain knowledge, and meet interesting people. Earlier research has shown that perceived quality of life significantly influences persistence and cognitive thinking (Aitken, 1982; Higgerson, 1985).

2.11.1.2 Approaches

The revised Bloom's flourishing academic allows for retrospective evaluation and individual thinking of a specific task level influencing grades, pass rates and persistence (Oliver & Dobele, 2007), as illustrated in Figure 2-19.

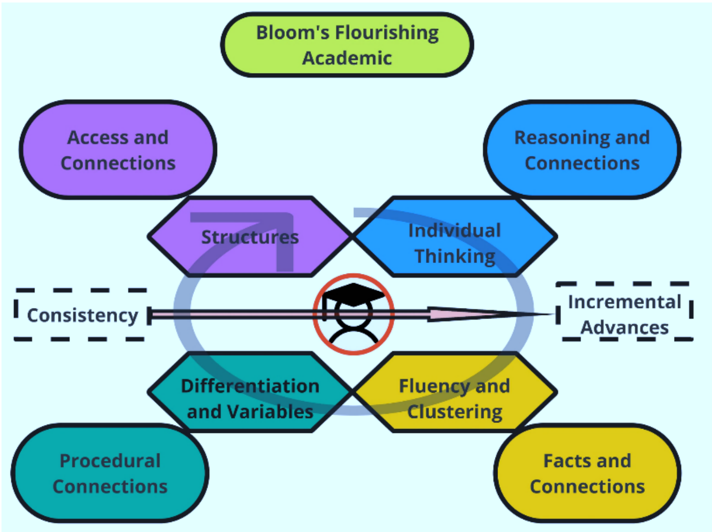

Figure 2-19 Bloom's: The Flourishing Academic (Bloom, 1984)

In his studies, Bloom (1984), a flourishing student illustrated in Figure 2-19, reported that students receiving one-to-one tutoring achieve academic performance two standard deviations higher than those receiving instruction via traditional methods. However, due to limited resources and associated costs, personalised one-to-one learning is impractical on a societal level (Jose, 2021). Recent advancements in machine learning present a promising avenue for personalised learning (Daimari et al., 2023). Artificial intelligence (AI) promises to unlock the full potential of one-to-one learning by helping the development of applications that offer customised instruction to each student (Barramuño et al., 2021).

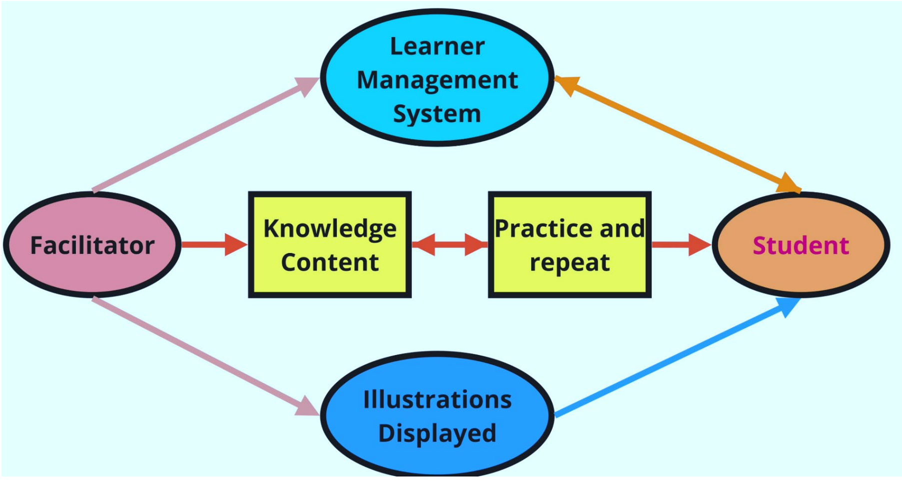

Figure 2-20 Traditional Teaching Methods (Bloom, 1984)

As seen in Figure 2-20, the traditional teaching approach involves delivering lectures to students while occasionally assessing them on the material. This conventional lecture method typically affects one instructor and at least thirty students.

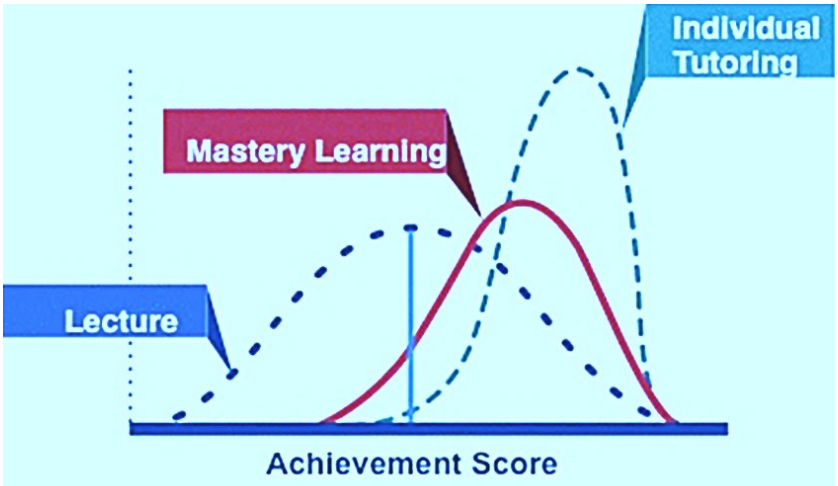

Figure 2-21 Mastery Learning Bloom (Bloom, 1984)

In contrast, Mastery Learning, illustrated in Figure 2-21, follows a similar approach to established lectures with the benefit of seminal tests that supply advice and direction to students in remedying misconceptions about the material (Guskey, 2010). Master Learning was instrumental in how Bloom (1984) described feedback. Alternatively, individual tutoring involves one-on-one instruction between a single student and an instructor. This approach includes formative assessments, feedback-analysis measures, and analogous seminal tests like those in Mastery Learning classes. Bloom (1984) supplies a summary of the research outcomes in one-on-one instruction as follows:

- Based on the control class's standard deviation, one-to-one tutoring elevates the average student's academic performance by approximately two standard deviations. Specifically, the stable lectured student typically exceeds 98% of students in the control group.
- In contrast, students enrolled in Mastery Learning classes achieve academic performance approximately one standard deviation higher than the regular student in the control class. On average, these students outperform 84% of students in the control group (Bloom, 1984).

The finding directed Bloom (1984) to postulate the 2-sigma problem, where he suggests that instructional cues increase student participation and may aid instructors in bridging the two standard deviation differences between one-to-one tutoring and conventional teaching methods.

In addition to the mastery learning by Bloom, Adaptive Learning Technology (ALT) enables students to enhance their comprehension and assume ownership of their academic growth proficiency White (2020), as illustrated in Figure 2-22.

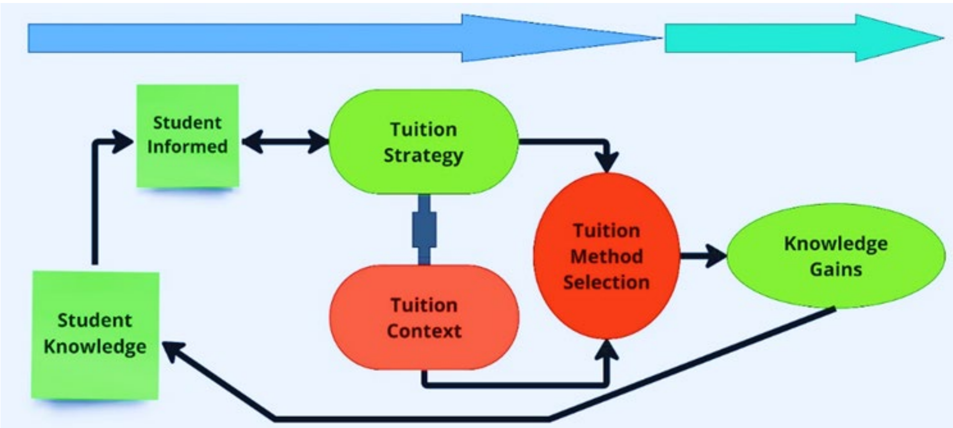

Figure 2-22 Modified Adaptive Tutoring Learning Effect Chain (Sottilare et al.,2018).

Table 2-12 Challenges Adaptive Learning Technologies

Challenges Adaptive Learning Technologies
Algorithmic Bias: AI algorithms may perpetuate biases, resulting in unfair treatment and discrimination of certain groups of students, affecting their academic performance.
Limited Personalisation: AI programs might not effectively assist students in reaching their academic objectives if they do not consider each student's unique learning preferences and styles.
Restricted dataset access: Machine intelligent foresight strategies or precision estimates, one of the concept's components, require much data to navigate. As with any educational data, it is often the case that data may not be readily available upon completing the learning and teaching processes.
Complexity in interpreting AI-generated insights: Because of the complexity of the algorithms, the insights derived from these processes may not be comfortably understandable to teachers and learners, thus resulting in less-than-good outcomes.
Extended dependency on AI systems: Learning under systems where Artificial Intelligence has dominion over students' learning process and output lowers their capability to reason and make wise decisions; hence, expect a poor showing.
Technological infrastructure limitations: This investigation also explored how insufficient technical equipment like devices or an unstable internet connection can cause learners to strain while applying AI-based tools and platforms to improve their performance.
Lack of teacher training and support: Deficiency in proper professional development programs which enlighten educators with knowledge on the appropriate way to adopt AI in their teaching and learning processes could also lead to the failure of implementing and enforcing the AI technologies and tools, hence affecting students as stated by (Alenezi et al., 2023).
Ethical considerations: Ethical issues, the violation of privacy rights, the security of the data, and the proper use of students' information remain subproblems that persistently complicate the AI application since a responsible and fair solution is required.
Cost and resource constraints: Training of the AI systems and their installation and support usually call for some funding and technical know-how. Hence, it may not be easily accessible to every learning institution. This drawback can impede the spread of such models and may even contribute to increased social disparities in all institutions. This limitation can hinder widespread adoption and potentially exacerbate existing inequities.
Adaptability to diverse student needs: The AI systems may have some difficulties adapting to the student-caretaker ratio, learning disability, or learning different ability aspects of the learners. This limitation can be alarming as it affects their performance and other areas of learning that they are undertaking.

Adaptive Learning Technology (ALT) is instructional software developed to follow the student's characteristics and preferred learning methods, elicited through questions posed to the program. Allowing the students to have an internet connection will enable them to log in to ALT, thus enhancing their learning system and taking the upper hand in the learning process.

Therefore, if internet-based ALT is available, students can work on complicated systems, increasing the speed of future learning. This increased learning speed concurs with the earlier research on this kind of ALT, which can raise personalised learning profiles and academic achievement (Jonsdottir et al., 2015; Walkington, 2013).

Table 2-12 raises the challenges associated with adaptive learning technologies. Promoting AI use in learning environments raises the following issues affecting the learners. Algorithmic bias, hence, will only continue this prejudice and, thus, negatively impact students' performances. The below-mentioned lack of individualised learning experience means that AI can't map its learning methods to the specific learning requirements that one might have, and restricted data sets can hamper impression accuracy. Some of the findings may be highly complex, making it difficult for educators and students to interpret the generated insights and, hence, less improved education strategies. A significant drawback of relying on AI is the weakening of cognitive abilities; technological infrastructures and inadequate preparations among teachers hinder the enhancement of AI use. On the ethical side, there is an issue with adequate protection of particular data and their security regarding AI use. Lastly, due to high costs and much-needed resources, AI implementation might not occur, contributing to the increasing gap between traditional and technology-enhanced education. Last but not least, another issue is the flexibility of AI in addressing all students, especially disabled students, as this poses a threat not only to learning achievements but also to learning experiences.

Adaptive Learning Technology (ALT) offers significant advantages, including addressing the diversity of student background knowledge and optimising class time by pinpointing areas needing additional support. ALT offers current content and facilitates diverse and active learning environments (Kakish & Pollacia, 2018). Nevertheless, using ALT is arbitrary and more effective in some subjects than others. Liu et al. (2017) identified that although ALT did not enhance the self-esteem of chemistry students, it did improve the students' opportunity to meet their knowledge needs. Nevertheless, learning in-class delivery was relatively less effective in meeting the learning needs of students in Biology, Mathematics, and Information Literacy. Dounas et al. (2019) pointed out the necessity of further investigation to explain the poor results of ALT in certain subjects. They appreciated various deficiencies in the system that might affect students' perceptions, attitudes, and performance. There is a clear indication that ALT needs to be modified and improved constantly to suit the needs of learners as they engage in their disciplines.

Underlying these existing teaching approaches are the frameworks that predefine the constructs that could drive grade and pass rate improvement using AI peer-to-peer support.

2.11.2 Grades and Associated AI Problems

Table 2-13 offers an overview of relevant problems related to AI and grade and pass rate performance.

Table 2-13 Problems Associated with Academic Performance and AI

Problem	Description
Algorithmic Bias	AI algorithms may perpetuate biases, resulting in unfair treatment and discrimination of certain groups of students, affecting their academic performance.
Limited Personalisation	AI systems that do not account for individual learning styles and preferences may not effectively support students in achieving their academic goals. Course content, standards, and outcomes from prior periods may differ from current periods. The learning and Teaching techniques of lecturers are different. Lecturer key performance measurements and their effect on final grades are potential limitations and are not part of the study.
Restricted dataset access	AI systems may require significant records to make exact projections and recommendations, but in learning and teaching, such data may not be readily available or accessible.
Complexity in interpreting AI-generated architecture	AI-generated insights may be challenging for educators and students to interpret and act upon, leading to suboptimal outcomes.
Extended dependability on AI systems	More reliance on AI systems may reduce students' thinking and decision-making skills, negatively affecting their academic performance.

Biased algorithms give some students unjust treatment and discriminate against poorly performing students compared to their counterparts. The lack of personal activities in AI interfaces can be ineffective in educating individuals according to their learning ability and inclination. Other factors that complicate the issue include differences in curriculum and coursework, standards and outcomes across periods, and the lecturers' teaching methodologies and styles. An area not part of this study is the effect of using grades and pass rates in faculty lecturer evaluations to assess key performance indicators. Further, there is the challenge of translating the insights from AI in a way that is beneficial for educators and students, as this can result in less-than-desirable consequences for all parties involved.

Lastly, over-dependence on AI systems may harm students' performance quality as it provides them with access to materials and fosters their thinking and decision-making skills. Frameworks like the Theories of Retention and Attrition guide the integration of AI peer-to-peer support within existing peer support structures (Tinto, 1975; Bean, 1980).

2.12 Literature Discussion

Lecturers are concerned with how AI platforms influence learning interest and achievements, hence high dropout rates in higher learning institutions (Del Bonifro, 2020; Guarda et al., 2023). One means of promoting this cause is by employing academic computational support systems that aim to increase students' retention and theoretical performance (Nicoletti & de Oliveira, 2020). Nonetheless, developing such systems has been difficult because of the nature and specifications of different domains Lema et al., 2023).

The focus of this study appears from this question: How do the features of AI, specifically as a facilitator of peer-to-peer interaction, enhance student retention and academic achievement and affect the student belief system? There needs to be more clarity between the feasibility of mass learning and teaching and the growing need for individualised instruction (Massar et al., 2023). This conflict underscores the need to balance the benefits of individualised learning and teaching with the practical challenges of implementing such a system (Minn, 2022).

The persistent challenge of improving achievement and retention rates in large classrooms Elibol & Bozkurt (2023) and the shortcomings of Learning Management Systems (LMS) in catering to individual student needs Zhang (2020) serve as the backdrop against which this research unfolds. These challenges, together with the role of student belief systems in academic achievement, frame the scope of this study.

The bibliometric literature review identifies gaps and examines AI's effects on student retention, achievement, and engagement by section. However, existing literature often overlooks AI's role as a peer-to-peer support facilitator, as identified in the gap section analysis. Each section explores a distinct aspect of AI's learning and teaching role.

The theoretical frameworks guide the conceptual framework and serve as a sieve to construct the framework of multiple interrelated components. They quantitatively capture different facets of the learners' engagement level and the achievement of the platform (Bohrnstedt & Marwell, 1978; Bacharach, 1989).

Compared to the framework provided by Eisner (2017), regarding the possibilities offered by qualitative research, one may safely say that it is crucial for understanding the position of AI in peer-to-peer learning. Studies in this regard have looked at how AI changes learning and teaching models and have delved into such aspects as learners' actions, engagement, and learning outcomes influenced by the application of this paradigm. These papers review diverse aspects of AI, including enhancing the collaborative learning environment and analysing the effect of AI on students' achievement, which helps readers grasp the complexity and essentiality of integrating AI in LMS.

Previous studies have pointed out the positive correlation between students' interaction with AI and their success rate (Wekullo, 2023; Tight, 2019; Shi et al., 2023). It has captured AI's possible impacts to enhance the quality and delivery of systems of higher learning (Minn, 2022). But unbefitting and unpredictable academic policies are among the most crucial student concerns (Shafiq et al., 2022). Therefore, this research envisages narrowing those gaps by contemplating a more purposeful way of implementing AI in teaching and testing students' sense-making concerning AI.

AI's role as a facilitator in peer-to-peer learning reveals three key outcomes: Self-belief in acquiring knowledge and participation to improve and transform academic performance and AI peer partnership. These outcomes include high dropout rates, a poor LMS system, and inconsistent academic policies, among other areas of concern. Solving these problems with the help of AI-assisted peer-to-peer support could decrease dropout rates, improve the efficiency of the LMS, unify educational standards, and improve learning conditions. All of the above objectives are backed up with each case by the supporting literature, thus providing an academic foundation for the study.

In the context of an AI peer-to-peer support platform, it is vital to address the issue of peer-to-peer support systems (Mitchell, 2023). Prevalent learning and teaching quality frameworks should consider this aspect. The peer-to-peer support practices depict the students as an asset and resource of the university with learning obligations towards their peers. This approach aligns with the institution's collectivist orientation. In an institutional context, a collectivist orientation emphasises group cohesion, cooperation, and collaboration among members instead of prioritising individual achievement or success.

The institution's values and beliefs revolve around the concept of individuals working together towards the common good of the group, with the success of the group being a shared responsibility. Cultures prioritising social harmony and community welfare over individualism and personal advancement are typically associated with this perspective (Mitchell, 2023). Through an analysis of school-based research, Mitchell (2023) proposes a taxonomy of peer-to-peer support practices. The significance of this investigation revolves around the degree to which Adaptive Artificial intelligence peer platforms engender a progressive impact on these practices, academic performance, and student retention.

The generalised Intelligent Framework for Tutoring (GIFT) has been deemed a significant breakthrough (Sottilare, 2011). GIFT is a domain-model, open-source platform that advances functionalities, including user modelling, authoring, assessment, and analytics. The modular architecture identifies and defines the learning objectives. It integrates AI knowledge like natural language processing, machine learning, and intelligent platforms. Integration enhances the system's functionality and capacity, offering students personalised learning experiences. The GIFT instructional management system considers individual differences, task demands, and cognitive and affective states to deliver adaptive instruction. Lecturers use this system to monitor and assess student progress in real time, adjusting lesson plans to meet changing needs. The GIFT system supports various teaching methods, including problem-solving, simulation, and game-based learning. It also gives feedback to students through written text, graphics, and multimedia.

Additionally, the system integrates intelligent agents and natural language processing technologies, enabling personalised interactions and feedback resembling human interactions. Ultimately, GIFT minimises cognitive overload and student annoyance, promoting engagement (Goldberg & Sinatra, 2023). GIFT supports mental, affective, psychomotor, and metacognitive learning objectives. The domain module, showing the principle of domain independence, contains all content specific to that domain. This approach encourages self-regulated learning using open student models, allowing students to choose their next step and track their progress and psychological attributes (Sottilare et al., 2018). The customisation enables instructors to create individual learning experiences, which can improve student retention and academic performance. His study presents a model for an Intelligent Tutoring System (ITS), an artificially intelligent peer platform to promote student learning, reduce attrition, and enhance academic performance.

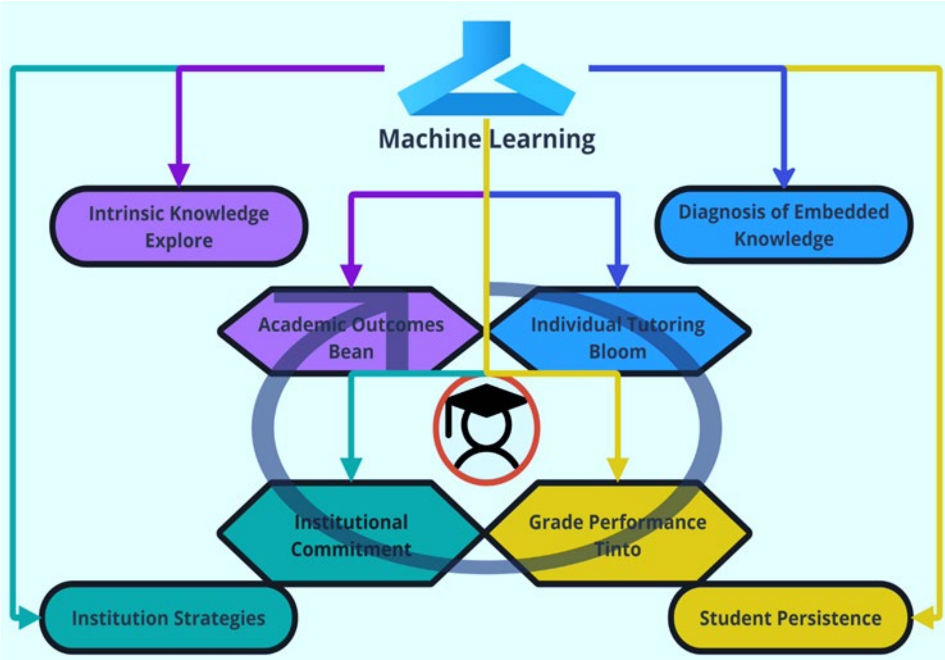

Figure 2-23 Architecture of Peer-to-Peer Support adapted (Bloom, 1984)

Figure 2-23, adapted from Bloom, illustrates a multi-faceted approach to machine learning and teaching, focusing on individual AI peer-to-peer personal tutoring (Bloom, 1984), Academic outcomes (Tinto, 1975), and goal performance and persistence (Bean, 1988).

2.12.1 Peer-to-Peer Support

Machine learning potentially enhances peer-to-peer support by establishing embedded knowledge within student groups (Trivedi, 2022). This analysis helps identify students who can provide tutoring and support to their peers, fostering a collaborative learning environment (Arco-Tirado et al., 2020). Machine learning algorithms should match students with complementary skills and knowledge by exploring intrinsic knowledge and promoting effective peer-to-peer interactions (Lainjo, 2023). These interactions promote understanding and foster uplifting relationships, camaraderie, and student cooperation (Maurya et al., 2021).

2.12.2 Engagement

Inserting AI peer-to-peer support into learning methodologies affects engagement (Zanker et al., 2019). By engaging student learning through the academic outcomes grounded in Bean's model, peer-to-peer support learning should examine students' engagement indicators concerning areas that require enhancement (Barramuño et al., 2021). Tech-supported peer-to-peer mentoring also fosters individual coaching, as evidenced by Bloom's taxonomy, which enhances student participation (Kem, 2022). Institutions can use these findings to create approaches with in-depth information to increase learner participation by focusing on the choice, learning, feedback and the path pursued by every learner(Hadjar et al., 2023).

2.12.3 Grades

Another region that AI peer-to-peer support is likely to influence is grade performance based on Tinto's model of student integration and persistence (Malmström & Öqvist, 2018). This integration can explain why, when exploring different factors that potentially influence grades, the researcher may unveil that AI peer-to-peer support can explain the students' outcomes and uncover specific patterns and tendencies (Lynch & Hennessy, 2017). At this level, this information helps lecturers apply appropriate teaching strategies and intervention methods to enhance students' grades (Einstein, 2023). Additionally, the AI-mediated individual tutorials supported through peer-to-peer could guarantee that students would get the attention required to perform academic tasks effectively, thus improving grade performance (Devi, 2023; Banna et al., 2015).

2.12.4 Pass Rates

Student persistence and pass rates are the intended outcomes influenced by the implementation of AI peer-to-peer support (Jones, 2023). To increase student retention rates, institutions should increase the institutional support for AI peer-to-peer support. Peer support enables early identification of at-risk students, preventing them from dropping out (Bowman-Perrott et al., 2023). Increased interaction, higher test scores, and strong peer support may help increase pass rates, thus increasing the number of students who complete their educational programs (Fahd et al., 2021). Integrating AI peer-to-peer support in these areas may lead to a more supportive, engaging, and effective educational environment, ultimately enhancing student success.

2.13 Conclusion

Intelligent AI peer-to-peer support platforms and lecturers could implement artificial intelligence and adaptive solutions into the learning process to increase student engagement, grades and passing rates by assisting them in returning. Some of the theories incorporated include Tinto's

(1975) student integration model, which evaluates social, academic and institutional data concerning the retention rates proposed.

For this reason, the conventional teaching style popular among many universities, such as teacher-centred classroom lessons compounded with paper-based tests, requires a rethink (Ellis et al., 2009). Modern learning trends promote using such approaches to learning as flipped classrooms that are interactive, student-centred, and personalised.

Students have achieved low results (OECD Indicators, 2018), and graduation and dropout rates have differed from country to country. Solving these problems presupposes using more effective and flexible approaches for students' demonstration of competencies required in the contemporary environment. Solving these challenges is impossible without using new pedagogy and andragogy that can help answer the modern learner's needs. Low retention and poor academic results have substantial societal and financial implications. Institutions implement student success programs to address these issues, including peer tutoring. It aligns with personalised learning and the flipped classroom model. It may only partially replace professional support and infrastructure, "AI can replace teachers/lecturers, data were obtained that 11% of students strongly agreed, 9% agreed, 23% disagreed, and 57% strongly disagreed regarding AI can replace teachers/lecturers" (Pratama et al., 2023: abstract).

The potential of adaptive AI in learning and teaching is promising but requires standardisation and further research. It builds on the historical development of AI, including Turing's concepts, the Turing Test and the pioneering work of Donald Bitzer and Joseph Weizenbaum. These contributions paved the way for modern conversational AI and intelligent tutoring systems. The AI peer-to-peer support platforms can use Bloom's taxonomy of learning, which aims to create tailored knowledge paths and assessments that align with students' cognitive abilities, knowledge levels, and learning styles.

In the methods part of this research, it is necessary to clarify how the literature findings reflect the formulation of the research questions. The questions will examine an AI platform's existing and real-life application, its effectiveness in making learning meaningful, relevant, and fair, and its possible role in improving the learning process. Through a detailed analysis of these aspects, the research will aim to unveil the dialectical shift in learning methodologies and achievement instigated by Adaptive AI.

CHAPTER 3 RESEARCH DESIGN AND METHODOLOGY

Researchers' ethnography[9] often guides their transition from theory to method selection, reflecting the understanding of individualised decisions in identifying problem areas (Schensul & LeCompte, 2012). This sociological imagination compels me to continually embrace variability and reconsider theoretical and methodological principles, especially in group dynamics.

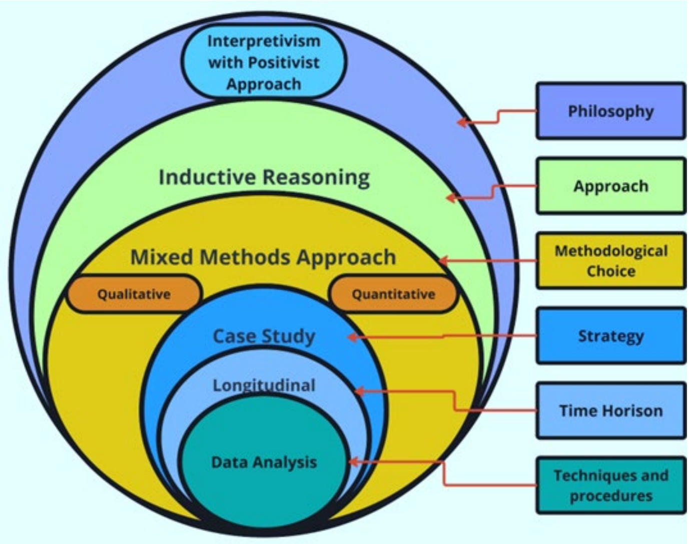

Figure 3-1 Study Design and Methodology

This reasoning underpins the use of an archival mixed methods case study in this research, which investigates the role of AI in peer-to-peer learning and its influence on academic performance and engagement, as illustrated in Figure 3-1.

3.1 Philosophy

The nature of learning outcomes that include multiple dimensions and factors makes adopting a dual paradigm approach in the given case study necessary (Kivunja & Kuyini, 2017).

9 “Ethnography is an approach to learning about the social and cultural life of communities, institutions, and other settings that, emphasises and builds on the perspectives of the people in the research setting, is inductive, building local theories for testing and adapting them for use locally andf elsewhere” (LeCompte & Schensul, 1999: 1).

Ontology studies existence and reality; epistemology concerns knowledge and the process of knowing. Both define the methodological context beginning with the researcher's positionality (Creswell, 2014).

3.1.1 Identity, Positionality, Biases and Mitigation of the Researcher

Positionality and reflexivity are crucial in any academic study and are particularly important in this work on AI-supported P2P learning (Wilson et al., 2022). As a researcher in this field and a lecturer in South Africa, I know the challenges of identity, positionality and reflexivity in the research process and outcomes.

3.1.1.1 Identity

Identity means the vocation, background, and context in which I work (Wilson et al., 2022). As a university lecturer and a PhD candidate, I believe that the respective academic and professional identity influences the methods used in this study. As a lecturer and a researcher, one gets to understand the learning processes and challenges experienced in the course of learning, especially in South Africa, where there are issues related to inequality in education and the use of technology in education.

3.1.1.2 Positionality

Positionality means knowing my biases in this research project (Wilson et al., 2022). As an academic in the South African education system, I am both an insider and an outsider (Dwyer & Buckle, 2009). This dual perspective helps identify the needs and potential implications of AI-supported peer-to-peer learning in the local educational context. The insider position offers good relations with universities; it also helps find participants and interpret the data in the context of culture. However, as with any such role, this one is not without its conflicts and battle of wits. This potential conflict leaves me responsible for ensuring I have no preconceived notions about the students and that the interaction with them does not influence the results.

In the context of this thesis exploring the effect of AI-facilitated peer-to-peer support on engagement, grades, and pass rates, potential biases could emerge from various sources, influenced by my academic and professional identity as a university lecturer and PhD candidate. These biases might impact the research design, data collection, analysis, and interpretation:

3.1.1.3 Biases

The discussion addresses possible biases, including confirmation, cultural and contextual, technology optimism, selection, interpretive, intervention, data, ethnocentric, role conflict, and outcome biases.

1. Confirmation Bias

- **Description**: As a lecturer with direct experience in education, particularly in South Africa, where educational inequalities are prevalent, there may be a tendency to seek or emphasise data that confirms pre-existing beliefs about the positive impact of AI on peer-to-peer learning.
- **Impact**: This could lead to selectively focusing on successful outcomes and overlooking or underreporting cases where AI integration did not significantly improve engagement, grades, or pass rates.

2. Cultural and Contextual Bias

- **Description**: My understanding of the unique challenges faced by South African students might lead to assumptions that specific AI-facilitated interventions are universally applicable or practical without fully considering the diverse socio-cultural contexts.
- **Impact**: This could result in generalisations that do not account for variability in student experiences across different regions, social groups, or educational institutions.

3. Technology Optimism Bias

- **Description**: A professional background focusing on technology in education might foster an optimistic view of AI as a transformative tool, potentially leading to overestimating its benefits.
- **Impact**: The thesis might inadequately address the limitations or challenges associated with AI in peer-to-peer learning, such as accessibility issues, technological literacy gaps, or resistance to technology adoption among students.

4. Selection Bias

- **Description**: Given my dual role as a lecturer and researcher, there might be a tendency to select participants or case studies that are more likely to demonstrate positive outcomes with AI-facilitated support.
- **Impact**: This could skew the results, making it difficult to generalise the findings to a broader population. For instance, selecting high-performing students or those more comfortable with technology might not reflect the average student's experience.

5. **Interpretive Bias**

- **Description**: My pre-existing knowledge and experience with educational challenges in South Africa might influence the interpretation of qualitative data. There might be a subconscious inclination to interpret student feedback in ways that align with my expectations.
- **Impact**: This could lead to an emphasis on narratives that support the perceived effectiveness of AI in improving engagement and pass rates while downplaying or misinterpreting criticisms or negative experiences.

6. **Intervention Bias**

- **Description**: My role as a lecturer might lead to an unconscious bias in how AI interventions are designed or implemented, emphasising methods that align with my teaching philosophy or that I believe will be most effective based on my experience.
- **Impact**: This could result in interventions tailored to specific educational contexts or teaching styles, which may not be universally applicable or practical for all students or learning environments.

7. **Data Interpretation Bias**

- **Description**: The dual perspective of a lecturer and a researcher might influence how quantitative data is interpreted, particularly regarding the significance and implications of changes in grades and pass rates.
- **Impact**: There might be a tendency to attribute positive changes primarily to the AI-facilitated support without fully considering other potential contributing factors, such as

changes in curriculum, teaching methods, or external factors impacting student performance.

8. **Ethnocentric Bias**

- **Description**: Focusing on the South African educational context could lead to an ethnocentric bias. I interpret findings through a lens prioritising this context's challenges and opportunities.

- **Impact**: This could limit the applicability of the research findings to other educational settings, particularly in regions with different educational structures, cultural attitudes towards technology, or levels of technological infrastructure.

9. **Role Conflict Bias**

- **Description**: Balancing the roles of lecturer and researcher might introduce a bias where the need to maintain credibility and authority in the classroom influences the research process, potentially leading to a more conservative or protective approach to reporting findings.

- **Impact**: This could result in underreporting challenges or limitations associated with AI-facilitated peer-to-peer learning to preserve professional reputation or avoid criticism.

10. **Outcome Bias**

- **Description**: The intention of the research to produce actionable and positive outcomes for improving student engagement and success may lead to a bias in interpreting the data, favouring the desired conclusions.

- **Impact**: This could lead to overemphasising the positive aspects of AI-facilitated peer-to-peer learning and underemphasising any neutral or negative outcomes, potentially skewing the study's overall conclusions.

3.1.1.4 Mitigating Biases

As part of the process to mitigate these potential biases, it is essential to adopt a reflexive approach throughout the research process. This reflexive process in this study includes where mitigation has been applied or not and explaining why:

- **Engaging in Regular Self-Reflection**: Continually reflecting on how your roles and experiences may influence the research (applied).
- **Triangulating Data Sources**: Using multiple data sources and perspectives to cross-validate findings (applied).
- **Involving Peer Review**: Seeking feedback from colleagues who may offer alternative interpretations (not applied; within this context, no other lecturers implemented this AI peer-to-peer support platform, limiting feedback from colleagues).
- **Ensure Transparency**: Document the research process, including any assumptions or potential biases (applied).
- **Adopting a Mixed-Methods Approach**: Combining qualitative and quantitative methods to provide a more balanced and comprehensive analysis (applied).

This way, I know about the positionalities which might be sources of bias for me and attempt to reduce the ethical consequences of the investigation.

3.1.1.5 Reflexivity

Given my experience and knowledge, I try to make the participants as diverse as possible to make the sample a true reflection of the population. Altogether, reflexive journaling was beneficial when collecting the data since it allowed me to notice and perhaps solve biases or assumptions (Braun & Clarke, 2019). To analyse the data, I applied an understanding of my positionality and reflexivity (Braun & Clarke, 2021).

To make the research logical and understandable, I explain how the methodological concepts of identity, positionality, and reflexivity apply to my study. It also makes the study more reliable and provides a significant appreciation of the relationship between AI, peer-to-peer learning and the educational environment. Hence, exploring and practising identity, positionality, and reflexivity is crucial when studying and integrating AI into learning through peer-to-peer collaboration. These elements help achieve realism, ethics, and orientation in educational settings in South Africa.

3.1.2 Ontological Considerations

An objective ontological perspective is also axiologically sustainable, allowing for measuring and reporting performance—such as student pass rates and scores, whether as percentages, ratios, or rates. The analysis of these results is backed up by AI frameworks, making it an interpretivist pragmatic paradigm research from my study. Interpretivism enables the incorporation of respondents' feelings as they relate to questions from the archival surveys, which encompass more encompassing beliefs and social environments (Maarouf, 2019).

3.1.3 Epistemological Insights

Epistemologically, objectification focuses on the reliability and credibility of the results of the archival study (Maarouf, 2019). Quantitative paradigms impose validity on the research and allow other researchers to follow them in the future. The rationale for using the pragmatic and interpretivism paradigm for this element is that the study describes events in its way while observing and questioning them, but at the same time, recognises that the context could affect the interpretation differently (Maarouf, 2019).

Therefore, this research adopts a mix of interpretivism and a pragmatic research paradigm to analyse the effects of AI learning platforms on students' performance in depth. Unveiling the assumption paradigm of the present study, a less stringent assumption that the data is from different distributions but specifying the mechanisms aligns with the study's focus on discovery over causality (Schölkopf *et al.*, 2021). It effectively outlines a complex, adaptable way of defining how AI interfaces with peer-to-peer learning environments, offering an ideal fit for interpretivism, a pragmatic perspective, and, to some extent, the assumption paradigm. This approach allows for an extensive range and scope while not overly constraining. Thus, using archival data in the study is methodologically appropriate for these paradigms' complex and subtle research questions.

3.1.4 Interpretivism Approach

Questions about students' belief systems and engagement are inherently subjective and complex, making them well-suited for an interpretivist approach. This study employs a QUAN method with a QUAL element (Creswell, 2014). Qualitative data can offer insights into how students perceive AI's usefulness, which quantitative data might only capture partially[10]. The grade data analysis for performance measurement follows the quantitative method. Combining the two methods lends itself to include a nuanced positivist approach.

3.1.5 Positivist Approach

The study employs the quantitative research approach centred on the empirical and quantifiable assessment of the effects of AI in peer-to-peer learning. It uses qualitative (QUAL) and quantitative (QUAN) indicators to create a conceptual model grounded in scientific evidence. It obtains data from other distributions derived from similar ones, implying that the model can be used in various settings and pushing out correct and authorised results (Schölkopf et al., 2021). The main research question focuses on the effectiveness of AI platforms, which needs to be measured and evaluated based on the results of implementing AI in peer-to-peer learning.

In this case, the approach follows the causality principle as postulated by Schölkopf et al. (2021). Schölkopf et al. (2021: Abstract) found to “review fundamental concepts of causal inference and relate them to crucial open problems of machine learning, including transfer and generalisation, thereby assaying how causality can contribute to modern machine learning research. A central problem for AI and causality is, thus, causal representation learning, that is, the discovery of high-level causal variables from low-level observations”. Nonetheless, this study does not directly investigate causality but contributes to the overall research goals of understanding causal mechanisms in AI and learning contexts.

3.2 Inductive Reasoning

This study uses general inductive reasoning to condense raw text data into a summary, establishing clear links between the research objectives and the summary findings (Azungah, 2018). The aim is to develop a model or theory about the underlying structure of experiences or processes evident in the raw data (Thomas, 2003).

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10 “The options available are multiple. We can decide not only what to use but how to prepare what we decide to use. How shall the vegetables be sliced? What proportion of each ingredient should be included? How should it be arranged?” Eisner (2017, p.18).

The interpretive elements aim to understand the nuanced experiences of students, particularly their beliefs and engagement levels, and grade performance data when using AI-assisted platforms. These questions require qualitative methods, where patterns appear from the archival survey data collected. The study explicitly acknowledges the scope and limitations of the archival questions in the survey; the questions relate specifically to the students who use the platform and their feelings on the use thereof. Understanding emerges from students' experiences and feelings, aligning with an inductive approach. While inherently qualitative and thus interpretive, archival survey data is guided by Froehlich et al. (2020) to a quantitative format using the literature and frameworks of (Tinto, 1999 & Bean & Metzner 1985). The inductive reasoning enables the generation of broader insights into students' engagement with the learning platform, incorporating the complexities of human experiences and belief systems into the data analysis.

Froehlich et al. (2020:1405-1406) state that while quantifying qualitative data to understand issues or trends, “opinions and beliefs are often expressed qualitatively in free text in issue-focused surveys” “to create a comprehensive dataset of assertions (claims, opinions, arguments, etc.) relevant to an issue”, “to provide a new approach for quantifying qualitative data for the understanding relevant to an issue”. This approach engaged students directly “to obtain and quantify qualitative information relevant to an issue” Froehlich et al. (2020:1405-1406) and then to rank the assertions by how strongly students support or oppose each of the assertions”. Assertions expressed by students provide vital insights into why an issue, like engagement, is relevant to this study. What aspects of the issue are students particularly enthusiastic about? Thus, organising assertions based on the amount of agreement and strength of support or opposition is particularly useful.

The grade data, on the other hand, is quantitatively analysed using a deductive t-test statistical method. Deductive reasoning usually involves starting with a general hypothesis or theory and then evaluating it through experimentation or observation. However, as in this study, using a t-test to answer a research question rather than a hypothesis still aligns with deductive reasoning. In this context, the research question serves a similar purpose to a hypothesis, guiding the analysis and interpretation of data. The t-test helps to determine if there is a statistically significant difference between groups, providing a concrete answer to the research question based on empirical data. Collectively, a data triangulation method is employed, accessing the literature and analysing engagement through the surveys and student performance through the final grades.

3.3 Methodological Choice

This study employs a mixed-methods approach to address the research questions effectively. The study provides a comprehensive view of AI's impact on learning by integrating quantitative data, such as changes in grades and pass rates, and qualitative data from student surveys on engagement. The concurrent collection and separate analysis of these data types, followed by their integration, allow for a thorough examination of objective outcomes and subjective experiences. This approach aligns with the complexity of the research questions and offers a nuanced understanding of how AI influences student engagement and performance.

Figure 3-2 illustrates two fundamental data types in this mixed-methods case study. Grades represent quantitative data analysed descriptively to measure performance. Student-perceived beliefs, analysed through reflexive thematic analysis and qualitative coding, serve as qualitative data measuring engagement. Reflexive thematic analysis (TA) takes an inductive approach, letting the codes and themes emerge from the data (Braun & Clarke, 2021). This type of thematic analysis is very flexible, allowing one to change, remove, and add codes. Reflexive TA emphasises the researcher's active engagement in reflecting on their assumptions, biases, and interpretations and how these may shape the analysis (Braun & Clarke, 2019). It typically involves iterative and reflexive cycles of coding, interpreting, and reflecting on data, intending to produce nuanced and contextually sensitive insights into the research topic while at the same time recognising and addressing the subjective nature of the research process.

Archival perception surveys (19), initiated in 2019, provide the source of qualitative data, focusing on student perspectives and engagement as components of a belief system. They are used as a starting point to consider what the aggregate data may imply about collective engagement as a part of a student belief system.

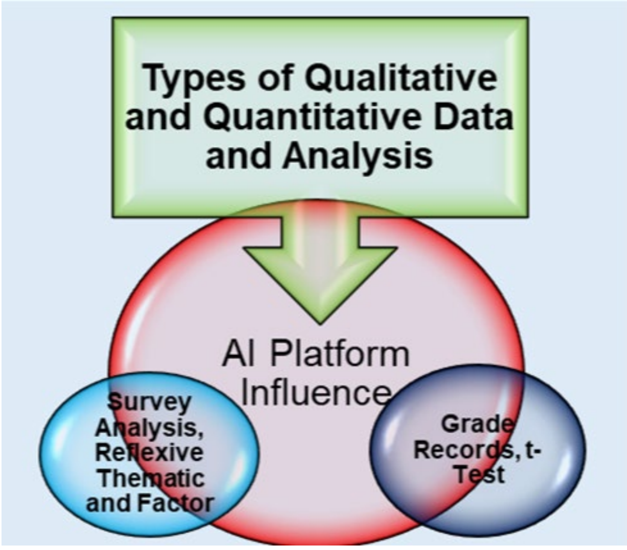


Figure 3-2 Types of Data and Analysis

Note that the archival questions, though broad, cannot capture every nuance or variable affecting student retention or engagement. Hence, there is a need for a mixed-methods approach.

3.3.1 Mixed Methods

The study employs a mixed-methods approach to address its research questions comprehensively. This methodology integrates quantitative and qualitative data, providing a more nuanced understanding of the impact of AI on peer-to-peer learning. The choice of a mixed-methods approach through four key points is outlined by (Lincoln, Yvonna S.; Guba, 1981):

1. **Validity and Reliability**: By combining quantitative data (e.g., grades and pass rates) with qualitative data (e.g., surveys on student engagement), the study enhances the validity and reliability of its findings. Quantitative data provides objective measures of academic performance, while qualitative data offers insights into student experiences and engagement. This triangulation of data sources ensures a more robust and accurate assessment of AI's effectiveness.

2. **Richness of Data**: The mixed-methods approach allows for a richer, more detailed exploration of the research questions. Quantitative analysis of archival data provides a broad overview of the trends and patterns, while qualitative data from surveys captures the subtleties of student attitudes and engagement. This combination offers a comprehensive view that neither method alone could achieve.

3. **Contextual Understanding**: Integrating qualitative and quantitative data helps contextualise the findings within broader educational theories and models. The study may offer insights into how technology influences learning experiences and outcomes by examining how AI affects engagement and academic performance. This approach supports a deeper understanding of the interplay between AI-assisted learning and peer-to-peer interactions.

4. **Theory Development**: Using mixed methods contributes to developing and extending theoretical models of AI peer-to-peer support in education. The study's findings will inform existing theories by providing empirical evidence on the effectiveness of AI in enhancing peer-to-peer learning and student achievement. This theoretical contribution aligns with the study's objective to advance knowledge in AI-facilitated learning.

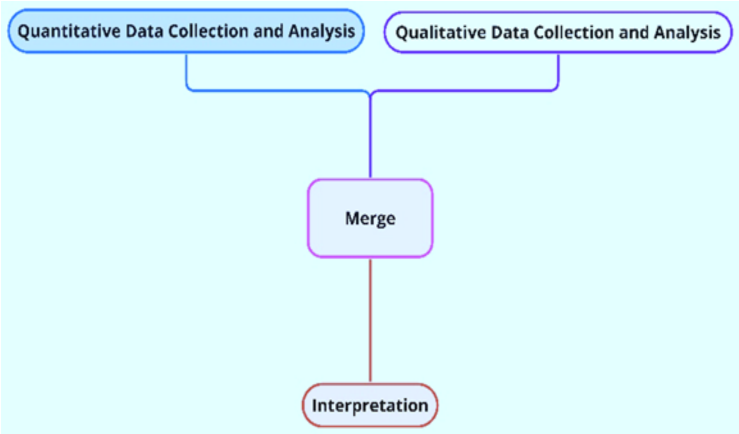


Figure 3-3 Convergent Method Design Diagram

In summary, the mixed-methods approach illustrated in Figure 3-3 is well-suited to address the study's research questions and objectives. This approach provides a comprehensive analysis by combining objective performance metrics with subjective engagement insights, ensuring a thorough examination of AI's role in peer-to-peer learning. The approach's validity, richness of data, contextual understanding, and theoretical development align with the study's goals and enhance the overall robustness of the research. A mixed-method approach is defined as "A methodology for conducting research that involves collecting, analysing, and integrating quantitative and qualitative research (and data) in a single study or a longitudinal program of inquiry" (Creswell & Clark, 2017: 5). Using this mixed-methods approach for this study combines quantitative data analysis (e.g., comparing grades and pass rates before and after AI intervention) with qualitative data (e.g., surveys on student engagement). Quantitative and qualitative archival data are collected concurrently but analysed separately, and the results are compared or combined during interpretation.

The method validates this study's findings, offering a holistic view of objective impacts and subjective experiences in AI-assisted learning platforms (Saunders et al., 2007). The data is cleaned using Excel, transformed, and standardised during the data preparation phase to ensure correct comparisons (Davis, 2010). Analysing student activity engagement reports (from the LMS and platform) and historical surveys will supply insight into student engagement levels. Metrics for this analysis will include the duration of platform use, engagement with the different platform features, and student responses to surveys examining their attitudes towards the AI-assisted learning platform (Davis, 2010). The design is basic exploratory Creswell (2014), as illustrated in Figure 3-4.

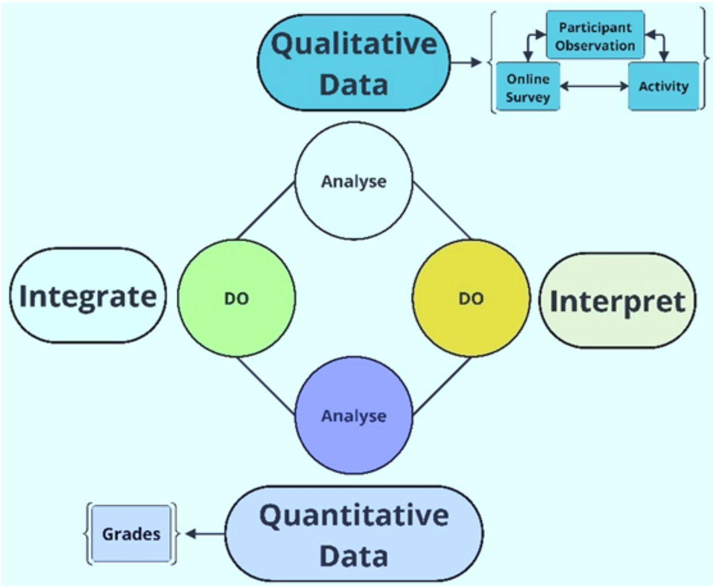


Figure 3-4 Basic Exploratory Design

This study integrates an inductive approach to examine the qualitative and quantitative data (Azungah, 2018). Finding future strategies to enhance student achievement and engagement is fundamental in addressing the research problem. This approach understands the interconnectedness of engagement and performance. A mixed-methods approach allows for a more nuanced understanding of factors at play, supplying both a quantifiable measure of AI's impact on learning and teaching and a qualitative learning of students' experiences and beliefs. This dual approach aligns with the complexity of the research questions and supplies a holistic view of the subject matter. The study aims to shape the content of the experience by providing categories and enhancing theories that define what is of interest[11]. Using qualitative data as a starting point, one could consider what the aggregate data may imply about engagement as a student belief and quantitative grade performance data[12]. Quantitative or qualitative results are insufficient by themselves. Collectively, the combined method offers more data and newer technology and is widespread. Initiatives often include multiple perspectives like personalised learning experiences, supportive peer-to-peer interactions, and validation. This initiative builds a comprehensive understanding and has better contextualised measurements. This cross-sectional case study design needs to explore the qualitative data before explaining the quantitative data.

3.3.2 Variables

Integral to the study is the independent variable AI platform, Connect®. Connect®, in Chapter 4, is introduced as an educational software application. It seeks to enhance student's learning and the quality of the course for both the students and the instructors. It improves the teaching delivery of courses for instructors (McGraw Hill Education, 2011). Figure 3-5, the 'Platform' represents the independent variable, while 'Engagement' and 'Grades' are dependent variables. This independent variable implies that the research relationship where the 'Platform' may be associated with variations in 'Engagement' and 'Grades'. It does not mean causation but instead explores correlations to support the

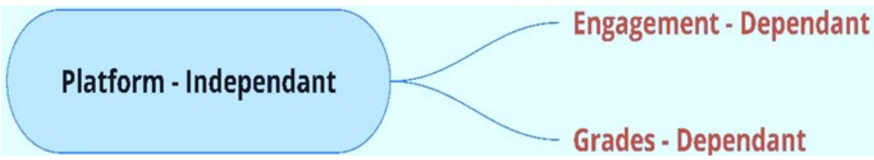


Figure 3-5 Dependent and Independent Variables

11 "Qualitative inquiry is not the property of any one discipline" (Eisner, 2017: 28).

12 Employing a multi-dimensional approach to metrics and indicators ensures a nuanced understanding of each research question. In the case of "student engagement," metrics such as attendance, time spent on tasks, and student feedback (questionnaires) are analysed. Note that the archival questions, though broad, cannot capture every nuance or variable affecting student retention or engagement.

research questions posited in the study. The study uses a conceptual framework[13] for the vital areas of interest: Engagement through surveys and activity levels and Academic Achievement through grades. The framework, illustrated in Chapter 2 may enable a multidimensional understanding of the issues, contextualising the archival data and platform features within broader academic discussions:

- Contextualising Archival Data: The framework aims to provide a nuanced lens for analysis. Aligning the questions with seminal models and theories enables the categorisation of responses into areas related to engagement, academic achievement and peer-to-peer learning. Therefore, the data is not just a 'standard evaluation' but part of a broader analysis within the scope of the study's research questions. The research objective frames the archival data to assess the AI platform's influence on engagement, academic achievement, and the facilitation of peer-to-peer learning.
- Multidimensional Metrics: The mixed-method approach ensures a more comprehensive understanding that is more significant than the sum of its parts.
- Longitudinal Analysis: The period from 2017 to 2023 provides depth to examine trends and themes over time, giving a more nuanced insight into how AI and peer-to-peer learning might influence engagement and achievement, even if causality is not the study's primary aim. The same lecturer instructed students with traditional methods and the AI platform, ensuring comparative data sets and deeper analysis.
- Extending Theoretical Models: The study contributes to theoretical extensions incorporating modern technology into classic learning and teaching models by correlating AI-facilitated learning with student outcomes.
- Qualitative-Quantitative Synergy: The qualitative data from opinion polls focuses on student beliefs and engagement, which are crucial components that contribute to the multidimensional nature of student engagement and achievement. The qualitative data complements the quantitative grade metrics, enhancing the analysis. The archival status of the surveys suggests that the data is naturally occurring.
- Study Objectives**:** The study looks to contextualise and interpret data to contribute to

13 Eisner (2017, p.33) said a qualitative study is “nonmanipulative, that is, it tends to study situations and objects intact, and it is naturalistic”. This study uses the existing archival surveys. Further, he said an investigation must relate “to the self as an instrument” (Eisner, 2017: 33). “The self is the instrument that engages and makes sense of the situation. This is often done without an observation schedule” (Eisner, 2017: 34).

practical applications and theoretical frameworks in learning and teaching.

It is not a matter of checking behaviours but of perceiving their presence and interpreting their significance. Related to the self-instrument is the positive exploitation of our subjectivity (Peshkin, 1988). This study does that, but not at the expense of anything. This study is interpretive by character, which is that it tries to account for what it is giving an account of. What accounts for the use of these platforms? Interpretation is the ability to explain why something is taking place. This study becomes believable because of its coherence, insight, and natural instrumental utility (Eisner, 2017). This naturalisation means seeing things from a point of view that will be adaptive to the adopted goal. This study can be qualitative by degree; something is not one thing or another. Academic grades from 2017 to 2022 provide quantitative data addressing student achievement.

This study uniquely focuses on AI's role in peer-to-peer learning—distinct from general IT-related teaching systems. While other studies regarding technology, learning, and teaching may exist, the scope here zeroes in on peer-to-peer facilitated by AI. Therefore, it advances beyond the over-researched arena of general IT efficacy in learning and teaching. The study seeks recurring themes or patterns within the archival data and platform features aligning with foundational peer-to-peer learning aspects. For example, if the archival data shows AI enhances individualised learning experiences, argue that this would logically extend to peer-to-peer scenarios. The study explores variables and the relationship between AI platforms without asserting causality but to ascertain the possible effect of the platform on grades.

Before investigating the intricacies of the engagement scale used in this study, it's imperative to grasp its significance within the broader research context. Measuring engagement is necessary for understanding how students interact with the AI-peer platform under investigation. It provides valuable insights into students' active participation, motivation, and overall experience, shaping learning outcomes. Triangulation is part of the method and design.

3.3.3 Data Triangulation

As the study merges qualitative with quantitative in a mixed methods design, data analysis from literature, surveys, and grades triangulates as illustrated in Figure 3-6. The data is analysed thematically and by factoring the data collected into categories. The grade data is statistically analysed.

Combining the qualitative data analysis technique of thematic coding with the quantitative data analysis technique of factor analysis and t-tests reduces the likelihood of inaccurate results. It increases the reliability of the study findings (Tashakkori & Teddlie, 1998). This integration assists in identifying the dimensions of qualitative data, thus making the intricate relationships between the variables more comprehensible. Applying factor analysis to coded qualitative data can also offer a quantitative way of analysing the data that is reliable and valid (Maxwell, 2012). These concepts suggest that the qualitative and quantitative data analysis methods are complementary rather than opposing.

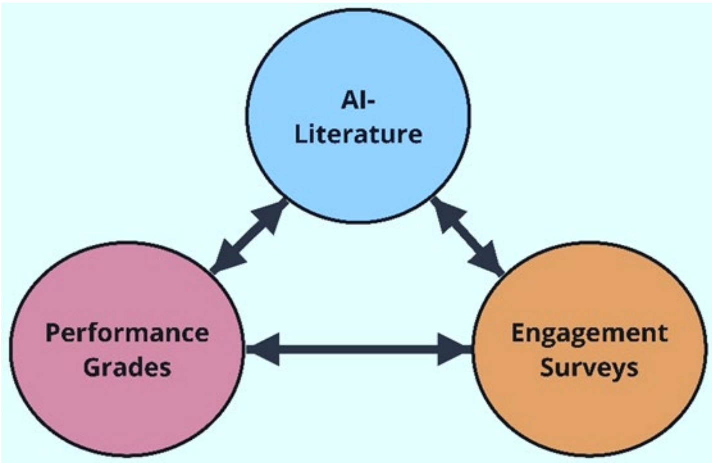


Figure 3-6 Triangulation

The existing literature on this topic also supports mixed methods since it allows researchers to understand the advantages and disadvantages of single-method approaches (Jick, 1979). Studies have shown that behavioural psychology comprises components, including methodology, theory, research activities, and social perspectives (Cozby et al., 2012).

Using the relevance theory, Denzin (2017) argued that his research methods have theoretical relevance, and each method has a unique relevance theory. He contended that sociologists could only make considerable progress in developing substantive sociological theory when they adopt a consistent and viable framework for analysing theory and method together. Denzin (1978) characterised triangulation as using various methodologies to study the same singularity. This approach is part of a distinct tradition within the literature on social science research methods that emphasises the value of employing multiple techniques, commonly referred to as concurrent methodology, multimethod, convergent validation, or triangular approach, as illustrated in Figure 3-6. This methodology forms the basis of this study's basic design, discussed in section 3.4. There must be a relationship between engagement and performance, performance must not precede engagement, and relations other than engagement and performance are excluded or do not give a better explanation (Denzin, 1978). According to Denzin (2017), the theory is an integrated set of proposals that help explain social phenomena. Its primary function is to provide structure and understanding to research activities.

The application of data triangulation as a research method yielded a richer and more in-depth data set. Data Triangulation enhances the study's rigour and validity, warranting its use in future research. Flick's (2022) work discusses Denzin's (1978) four types of triangulations, illustrated in Table 3-1.

Table 3-1 Types of Triangulations (Denzin, 1978)

Type	Description
Data Triangulation	It uses multiple data sources from contrasting times, places, and people to enhance research validity.
Investigator Triangulation	Employs multiple researchers in data gathering and analysis to mitigate individual bias and subjectivity.
Method Triangulation	Combines one or more research techniques into a particular strategy or at different levels to evaluate a phenomenon.
Theory Triangulation	It enhances the possibilities of searching for data and creating new knowledge by presenting analysis within the framework of multiple theories.

This table summarises Denzin's four types of triangulations, validating research findings through different lenses, methodologies, and perspectives.

- Data triangulation involves the systematic and purposeful utilisation of different data origins, such as contrasting times, places, and people, to involve multiple study groups and settings in the research.
- Investigator triangulation involved using more than one person in the data gathering and analysis processes to compare their influences on the research issue and outcomes.
- The triangulation could include using multiple methods within the same approach or diverse ways to approach the same phenomenon.
- Theory triangulation in this research context involves analysing data from various theoretical frameworks, perspectives and hypotheses to expand the potential for

generating knowledge.

The data triangulation offers a comprehensive understanding of the research question: When implemented, how does an AI-assisted learning system influence patterns in academic performance and beliefs about platform engagement? The triangulation relevance theory provides a foundational structure to explore potential patterns and correlations within the method employed. The research design adopts an inductive relevance approach to address the case study design.

3.4 Case Study Design

Yin (2003: 13) defines a case as “a contemporary phenomenon within its real-life context, especially when the boundaries between a phenomenon and context are unclear, and the researcher has little control over the phenomenon and context”. This study applies this strategy by Yin (2009), which aligns interpretivism with a pragmatic approach to assess the influence of an AI-assisted platform on engagement and performance. He defines a case study as “an empirical inquiry that investigates the case or cases conforming to the abovementioned definition by addressing the “how” or “why” questions concerning the phenomenon of interest” (Yazan, 2015: 148).

This case study is an in-depth study of data from a university database of a cohort of students comparing data pre-platform and post-platform over 2017-2022. Quantitative data from historical grades evaluates the platform's (dependent variable) influence on academic grades (independent variable). The survey's qualitative data assesses student perceptions and engagement levels (independent variable) with the platform (dependent variable). By analysing these data streams separately and merging them, the study aims to provide a comprehensive understanding of how the platform affects student performance and engagement at the university level (Yazan, 2015). This strategy prioritises ecological validity, studying the effect in a natural learning and teaching setting (Zawacki-Richter et al., 2019).

3.5 Longitudinal Time Horizon

“It is essential that the methods of data collection and recording are identical across the various study sites, as well as being standardised and consistent over time. Data must be classified according to the interval of measure, with all information pertaining to particular individuals also being linked by means of unique coding systems” (Caruana *et al.*, 2015: E538).

This longitudinal case study uses two data sources (Yazan, 2015). The first source records student grades from 2017 to 2019, relying on traditional instruction without the AI-assisted platform (Eisner, 2017). The second source involves students who used the AI-assisted learning platform from 2020 to 2022. Notably, all students from 2017 to 2022, whether they had access to the platform or not, followed the same course outlines, goals, and attributes.

Longitudinal research can be of various types depending on the design and duration of the study (Neale, 2020). They are mainly descriptive studies but can also be causal (Caruana et al., 2015). This shared research technique in a longitudinal study involves monitoring the subjects at varied intervals (Neale, 2020). These may include:

- Cohort panels are a subset of a defined population that exhibits some or all of the exposure or outcomes of interest followed over time (Yin, 2009).
- The sampling of data frames at regular intervals (Yin, 2009).
- Data collected for other purposes is tapped and linked to generate individual-level data sets (Yin, 2009).
- A retrospective study is a type of research in which some participants must have experienced specific events. After that, the data about the exposure of a particular cohort is collected and analysed (Yin, 2009).

Table 3-2 illustrates the advantages and disadvantages of longitudinal cohort studies, mainly conducted prospectively to the fullest extent (Caruana *et al.*, 2015).

Table 3-2 Advantages and Disadvantages of a Longitudinal Case Study

Advantages	Disadvantages
The ability to recognise events and connect them to specific exposures, elaborating on them in the context of presence, time, and duration (Yin, 2009).	Non-adherence and loss of participant follow-up lead to potential consequences on sample representativeness if due to a specific exposure or event (Yin, 2009).
The capacity to adjust for cohort effects, considering the age range of subjects, period of data collection, and the age of subjects at the time of data collection, and the impact of each on the results (Yin, 2009).	Ambiguity in separating the effects of exposure on the outcome impact, especially when they reinforce each other and when the period between exposure and outcome is lengthy.
“Establishing sequence of events”(Caruana et al., 2015: E537).	Increased temporal and financial resources are required to implement this approach (Yin, 2009).
“Excluding recall bias in participants, by collecting data prospectively and prior to	“The potential for inaccuracy in conclusion if adopting statistical techniques that fail to

knowledge of a possible subsequent event occurring" (Caruana *et al.*, 2015: E537).	account for the intra-individual correlation of measures" (Caruana *et al.*, 2015: E538).
"Ability to correct for the "cohort effect"—that is allowing for analysis of the individual time components of cohort" (Caruana *et al.*, 2015: E537).	

" Longitudinal methods may provide a more comprehensive approach to research, that allows an understanding of the degree and direction of change over time" (Caruana *et al.*, 2015: E539). There are inherent difficulties to this type of study design, compounded by the fact that the collection is over a long period. As the data covers six years, the study follows a thematic, factoring and descriptive procedure for analysis.

3.6 Data Analysis Techniques and Procedures

Thematic, Factoring and Statistical analysis are employed to analyse the qualitative and quantitative data.

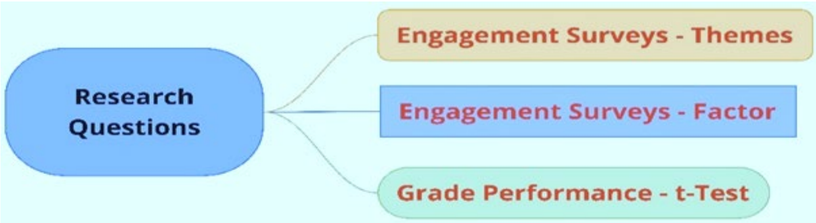


Figure 3-7 Statistical Methods.

Figure 3-7 represents the research's central analysis to answer the research questions. The significant node, 'Research Questions', signifies the primary research assertion from which the analysis methods emanate. The process commences with the population and sample size.

3.6.1 Sample Population

The study focused on a sample of archival grade data collected from 2668 records in a single department (Management and Project Management) from a cohort (Financial Management) in the Faculty of Business Management and Sciences at a university in Cape Town, South Africa, from 2017 to 2022. The selection criteria within the specific department are non-random, focusing specifically on whether students use the AI platform. However, when viewed from the perspective of the entire university, this choice is random. These criteria are applied to archival data from the specific department during the mentioned period (Alvi, 2016).

The sample size for each year averaged 534 students registered and 206 responded. Acknowledging that this dataset pertains solely to one institution and may not comprehensively stand for the learner population across different institutions is imperative.

3.6.2 Sample Size, Justification, Power Analysis and Adequacy

Measuring student engagement through a quantitative instrument in face-to-face courses is challenging, and the complexity increases in the context of blended learning and virtual classrooms (Robinson & Hullinger, 2008). In their study, Robinson & Hullinger (2008) employed a qualitative redesigned National Survey of Student Engagement (NSSE) study, a reputable research project, to assess student learning and engagement levels (Loo et al., 2018).

In their findings on student engagement in online learning, Sher (2009) used two different surveys for evaluation. Dixson (2010) highlighted the need for a standardised scale to measure engagement levels specifically for online students. The researcher distributed a link to students through the learner management system in this study and associated surveys. Data collection occurred automatically via Google Forms without personal identification information. Initially, I saved the data in .csv format and converted it to .xlsx for screening in Excel. To minimise entry errors, the researcher employed both Excel and SAS University Edition, readily available for statistical interpretation. Software programs screen the data for consistency. Upon completing data screening, the researcher uses SAS University Edition to conduct factor analysis, t-tests and correlation to address the hypotheses and research questions.

Addressing concerns about sample size in survey-based research, Beavers (2019) & Rahman (2023) suggest 150 to 300 participants as an optimal range for factorial analysis studies. Following this guideline, an average of 534 students participated in the survey, ensuring a robust sample size.

3.6.2.1 Justification

In survey-based research, determining an adequate sample size is necessary for ensuring the reliability and validity of the study's findings. In this study, an average of 534 students participated in the survey, which aligns with the guidelines suggested by Beavers (2019) & Rahman (2023), who recommend a range of 150 to 300 participants for factorial analysis studies. However, power analysis provides a more robust justification beyond these general guidelines.

3.6.2.2 Power Analysis for Quantitative Components

To strengthen the methodological rigour, a power analysis was conducted to determine the minimum sample size required to detect a statistically significant effect. An alpha level of 0.05 and a power level of 0.80 were used for the power analysis, which is standard in educational research. The effect size was estimated based on previous studies examining the impact of peer-to-peer support on student outcomes (Sher, 2009). A medium effect size (Cohen's d = 0.5) was assumed to be a conservative estimate given the expected influence of AI-facilitated peer support on engagement, grades, and pass rates.

Using G*Power, a widely accepted software for power analysis, the required sample size for the study was calculated (Erdfelder et al., 2009). For a t-test (two-tailed), which will be used to compare means between groups, a sample size of 128 participants is needed to achieve a power of 0.80 with a medium effect size. For correlation analysis, with the same parameters, a sample size of 85 participants is required. Given that 534 students participated in the survey, the sample size far exceeds the minimum required, ensuring that the study is adequately powered to detect even more minor effects.

3.6.2.3 Adequacy of Sample Size in Context

The sample size of 534 participants not only meets the requirements of the power analysis but also provides sufficient data for the factorial analysis, thematic analysis, and t-tests planned in this study. This large sample size enhances the generalisability of the findings, allowing for more confident assertions about the impact of AI-facilitated peer-to-peer support on the broader student population. Additionally, the diversity of the sample, drawn from various courses and levels, further strengthens the study's validity. With data thus collected and screened, the study transitions to the following analytical phase employing thematic, factoring and t-tests to evaluate the data. These tools are needed to interpret the dataset and provide insights that build upon the foundational work of factorial analysis and correlation used in the survey analysis. Following this recommendation, the study gathers data from the various sources in Appendix 6 (A).

3.7 Data Collection and Analysis

The researcher collected the data from surveys, final grade performance results and pass rates from 2017 to 2023 from the Learner Management System and the institution's grades database. Table 3-3 maps the research questions to the data collection and analysis methods supporting the findings.

Table 3-3 Mapping Research Questions to Data Collection and Analysis Methods

Research Questions	Data Collection Method	Data Analysis Method	Justification
MQ: To what extent does Peer-to-Peer AI support influence student engagement, grades, and pass rates?	- Survey distributed via LMS. - Engagement metrics from course data.	- Factor analysis - T-tests - Correlation analysis	These methods allow for a comprehensive analysis of the overall impact of AI-facilitated peer support across multiple dimensions.
RQ1: How do students perceive the influence of AI-facilitated peer-to-peer support on engagement as part of their belief system?	- Qualitative responses from the survey.	- Thematic analysis	Thematic analysis captures nuanced perceptions and attitudes, providing depth to understanding student engagement.
RQ2: To what extent does AI-facilitated peer-to-peer support enhance student grades by assisting students in their return?	- Grades from academic records. - Survey on AI support usage.	- Correlation analysis - Factor analysis	These analyses will measure the relationship between AI support and grade improvement, isolating the impact of AI support.
RQ3: To what extent does AI-facilitated peer-to-peer support influence pass rates?	- Pass/fail data from academic records. - Survey on AI support usage.	- T-tests - Factor analysis	T-tests and factor analysis will help determine the significance and strength of the relationship between AI support and pass rates.

Explanation

Table 3-3 aligns each research question with its corresponding data collection and analysis methods. The table justifies the selection of each method, outlining the study's design and reasoning. The research employs a mixed-methods approach, leveraging quantitative and qualitative data to analyse the impact of AI-facilitated peer-to-peer learning. Using surveys, academic records, and qualitative data enables an examination of how AI influences engagement, grades, and pass rates. Factor analysis, t-tests, and correlation analysis are used to interpret the data, providing insights into the relationships between variables and answering the research questions.

3.7.1 Method: Surveys

The survey was non-obligatory via the online Learner Management System. Appendix 3 and Appendix 4 illustrate the settings and questions, completed by a deadline with no late responses permitted. The researcher then analysed the data and securely recorded it in Excel, storing it in the university database, as shown in Table 3-4 and Appendix 6 (E).

Table 3-4 Information Collated into Excel for Analysis

Timestamp	How effective is AI in helping peer-to-peer interactions?	Does AI support help you keep course informati on?	Do you believe AI enhances your academic performa nce?	Does AI alter your perspecti ve about peer-to-peer learning?	Do you believe Connect offers better access to resources than a prescribed textbook?	Is AI-equipped peer-to-peer learning more engaging than traditional methods?	How reliable is AI in assessing peer-to-peer interactions?	feel AI provides a personali sed learning experienc e in peer-	Does AI influence your motivation in peer-to-peer learning?
2023/09/08 8:54:56 pm EEST	Effective								
2023/09/08 8:54:56 pm EEST	Effective	Sometime	Agree	Neutral	Agree	Neutral	Highly Reliable	Neutral	Moderately
2023/09/08 9:44:43 pm EEST	Effective	Always	Agree	Neutral	Disagree	Neutral	Neutral	Neutral	Neutral
2023/09/09 12:16:09 am EEST	Highly Effective	Always	Neutral	Not at all	Strongly Agree	Neutral	Reliable	Agree	Neutral
2023/09/09 12:33:15 am EEST	Neutral	Often	Strongly Ag	Not at all	Agree	Disagree	Reliable	Agree	Significantly
2023/09/09 8:43:14 am EEST	Effective	Rarely	Agree	Moderatel	Neutral	Neutral	Reliable	Neutral	Slightly
2023/09/09 10:27:29 am EEST	Highly Effective	Often	Strongly Ag	Significant	Strongly Agree	Neutral	Neutral	Agree	Moderately
2023/09/09 11:49:24 am EEST	Highly Effective	Always	Strongly Ag	Significant	Strongly Agree	Strongly Agree	Highly Reliable	Strongly A	Significantly
2023/09/09 12:25:28 pm EEST	Neutral	Often	Disagree	Neutral	Strongly Agree	Strongly Disagree	Not Reliable	Disagree	Not at all

Eisner (2017, p.33) said a qualitative study is “nonmanipulative, that is, it tends to study situations and objects intact, and it is naturalistic”. This study uses the existing archival surveys as its data instruments, maintaining its natural form. Further, he said an investigation must relate “to the self as an instrument” (Eisner, 2017: 33). “The self is the instrument that engages and makes sense of the situation. This is often done without an observation schedule” (Eisner, 2017: 34). Grade data is sourced differently via the university information system.

3.7.2 Method: Grades

Figure 3-8 illustrates the type of grade data the university information system holds, representing the final published marks from which the researcher collected the raw data. Appendix 6 (X) in the repository illustrates additional examples.

Cape Peninsula University of Technology

Pass Rates and Average Final Marks

Report Parameters	
Year	2022
Department	MANAGEMENT & PROJECT MGNT

Department	Period Of Study	Module	2022 Enrolments	Passed	Pass Rate	Average Final Mark
BUSINESS & MANAGEMENT SCIENCES						
MANAGEMENT & PROJECT MGNT	4	Purposely Blanked				
		FINANCIAL MANAGEMENT 4 (FNM470S)	76	63	82,9%	57
		Purposely Blanked				
		Purposely Blanked				
		Purposely Blanked				
		Purposely Blanked				
		4 TOTAL	375	261	69,6%	52
	MANAGEMENT & PROJECT MGNT TOTAL		**375**	**261**	**69,6%**	**52**
BUSINESS & MANAGEMENT SCIENCES TOTAL			**375**	**261**	**69,6%**	**52**
Report Total			**375**	**261**	**69,6%**	**52**

Report Definitions	
At risk modules	Modules with a pass rate that is less than the set target in the University enrolment plan of 79%
High impact modules	Modules with enrolments numbers above 100 and with a pass rate below 79% and/or average final mark less than 50%
On pass rates	
Green	Modules with a pass rate that is equals to or greater than 79%. These modules have met the national benchmark for pass rates
Yellow	Modules with a pass rate that is between 50% and 78.99%
Red	Modules with a pass rate below 49.99%. These modules sit far below the national benchmark.
On average final mark	
Red	Modules with an average pass mark below 50%

Figure 3-8 University-published Final Marks

The university has granted the researcher site approval to use all data sources available on the university information system, as illustrated in Figure 3-8, exclusively for this study. The approval letter is stored in the repository and accessed via Annexure 6.

After collecting the data, the researcher analyses it thematically using factor analysis and statistical t-tests.

3.8 Data Sources

I accessed the data from three primary sources within the institution's database: final published grades and pass rates data and the learner management system for the surveys from 2017 - 2022. These are the dependent variables. The independent variable, Connect®, is integrated into the learner management system and serves as the data source for the platform's features.

This study accesses nineteen surveys with 157 questions, alongside achievement data from five courses via the learner management system, as illustrated in Appendix 6 (B). Appendix 6 (T) provides historical data from surveys and activity reports. These reports offer insight into student interactions with the AI-assisted learning platform. Grade data offers final performance data for students. Analysing historical data from learner management systems supplies an empirical lens to examine the impact of AI-assisted learning platforms. The retrospective nature contributes to a natural, comprehensive understanding of how AI helps peer-to-peer learning and influences academic success. These inquiries investigate potential outcomes and implications, focusing on the possible effect of AI-driven interactions on student performance and engagement.

“It is incumbent on case study researchers to draw their data from multiple sources to capture the case under study in its complexity and entirety” (Yazan, 2015: 142). “Yin advocates the combination of quantitative and qualitative evidentiary sources because he views them equally instrumental” (Yazan, 2015: 142). Yin (2003) suggests merging data triangularly, including sources such as documentation and archival records. He further suggests the principles that apply to the gathering of data include “the use of (a) multiple sources of evidence (evidence from two or more sources but converging on the same set of facts or findings for triangulation), (b) a chain of evidence (explicit links between the questions asked, the data collected, and the conclusions drawn which helps” (Yazan, 2015: 142). Yin (2003: 83) says “follow the derivation of any evidence, ranging from initial research questions to ultimate case study conclusions”. The idea is to maximise the quality of the inquiry by drawing from maximum data sources. Figure 3-9 triggers the multiple sources and presents the origins of the data relevant to the research questions. It is crucial to present Connect® as the independent variable data source that underpins the research questions. Identifying the features of Connect® enables the mapping of AI as a peer-to-peer support intervention.

The collected data helps me determine the AI platform's impact on engagement, grades, and pass rates. The data sources include the Connect® platform, the final grade database, and the pass rates database.

3.8.1 AI Peer-to-Peer Support

Connect® is an educational software application that aims to increase student learning, improve the overall course experience for both the students and the instructors, and increase the effectiveness of course delivery for the instructors. Connect® provides a single location for all course materials, assignments, and quizzes, analytics that reveal student progress and performance, suggestions for how students can improve, and adaptive learning tools that tailor the learning process to the individual.

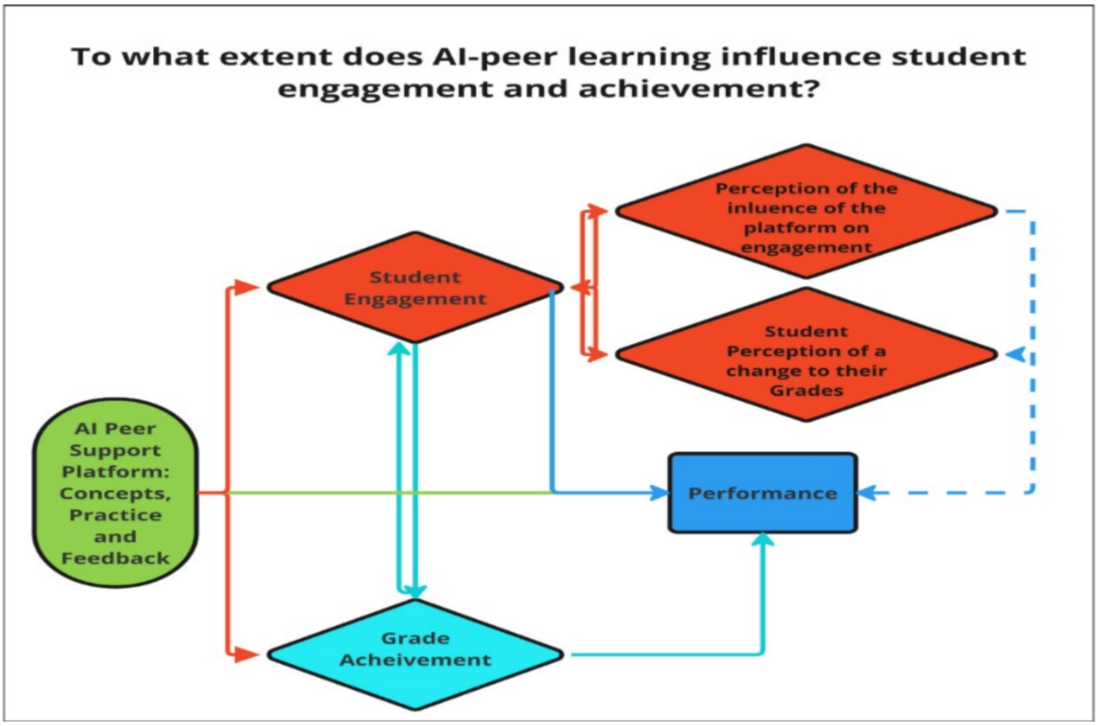


Figure 3-9 Flow of Study Applied to the Research Question

It allows educators to create custom courses using reading, homework assignments, lecturer-designed material, and assessments from over 90 subjects, and it integrates with other Learner Management Systems (LMS). Connect® users can also utilise SmartBook®, an adaptive learning and reading tool. SmartBook identifies urgent concepts for students to master and offers related resources such as videos and slideshows to help students meet the learning objectives. The starting point in Figure 3-9 is the AI Peer-to-Peer Support Platform Connect®. Three features of the platform are concepts, practice, and feedback. They purport to directly influence three main areas: peer-to-peer support, student engagement, and grade and pass rates as part of achievement and performance.

During the content organisation phase, lecturers discovered that adaptive courses require additional or alternative content compared to traditional methods (van Leusen et al., 2020). Although not extensively discussed in the literature, anecdotal feedback suggests that this feature improves the personalisation of adaptive courses (Hong, 2023). Throughout the lesson, the system encourages students to select a different example or instruction when presented with alternate content (Anson, 2023). Due to time and staffing constraints, however, only a tiny proportion of adaptive courses had alternate content or options generated.

To transition from the traditional course development paradigm to an adaptable one, instructors and course developers enhanced the learning and teaching content in the Learning Management System (LMS) by incorporating more text, specific examples, embedded videos, animations, and other resources illustrated in Figure 3-10. If the institution adopted the values of collective design for knowledge acquisition, it might accommodate the diverse learning preferences of its students. The availability of question sets, illustrations, and audio-visual aids enhances the quantity and quality of subject matter variation and benefits students who return to classes to connect with the relevant subject material, as seen in Appendix 6 (H).

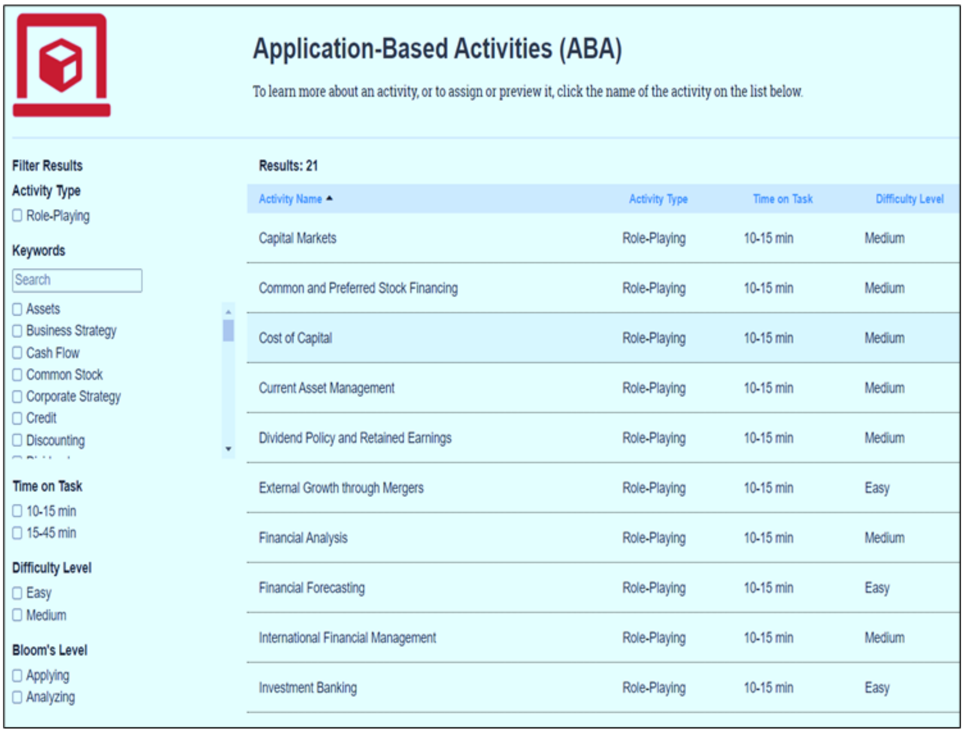


Figure 3-10 Alternative Content

This inclusion is helpful for learners revisiting classes for subject engagement. It leads to exploring the next step in refining academic performance: knowledge acquisition.

In developing content, Khosravi et al. (2022) emphasise creating assessment-driven learning activities arranged in a categorised format to ensure that students have mastered needed skills before advancing to more advanced topics. The adaptive process starts with knowledge determination, involving predetermined questions. It is crucial, however, to note that an adaptive system's configuration level varies across different platforms (Bobko et al., 2023). Depending on the student's performance, the system determines whether they require acceleration or remediation through a demonstrable learning passageway (Hatem, 2023).

It is important to note that the adaptivity of a system only exists in theory until a student interacts with it (Kamalov et al., 2023). As a student begins to interact with the system, it collects data on the learner's content preferences and aptitude level, determining the type and difficulty of material presented to the student. As the learner profile takes shape, the instructor can analyse the data trends and intervene to reinforce student mastery through content review and revision.

Figure 3-11 illustrates different course categories for analysis, depicting learning analytics; Appendix 6 (C) shows an additional example. Students progress along the learning path, and lessons become accessible on completion. This planning sanctions student choice while limiting their engagement with specific materials to certain points along the learning pathway. Custom objectives are employed to regulate the weekly pace of the curriculum. The platform categorises the knowledge-based requirements based on topics that have been previously learned and mastered and learning outcomes influencing the students' desire to remain in the course. The adaptive learning path also included learning analytics and instruction features. The adaptive courseware provided personalised feedback and delivered a comprehensive web of content, resulting in granularised data points for each student. Instructors could use this data to interpret students' duration in each learning discipline. Lecturers understand the effort they spend during that phase, raise any questions for review, or continuously attempt related questions without success. These limitations could be addressed during in-person sessions, allowing lecturers to tailor future lessons accordingly.

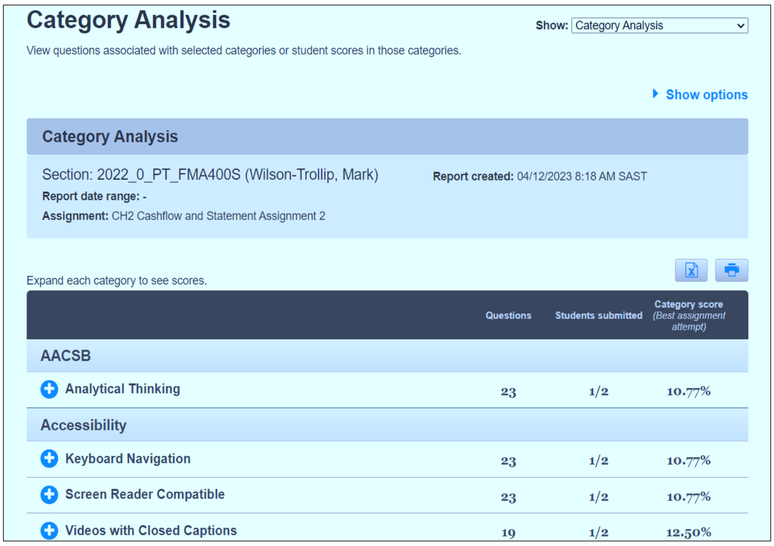


Figure 3-11 Category Analysis

Using student-centred learning analytics, one can set up peer-support groups (seminal frameworks) and implement interventions before academic issues become too challenging to address or irreparable. Figure 3-11 represents an example of a category analysis report. The success of this adaptive pathway is attributable to crucial factors involving the instructor's involvement in fundamental routine features. The objective-based embedded knowledge enhanced by the alternative content of this platform supplies the study with detailed examples of learning analytics in practice, as seen in Appendix 6 (F).

The AI platform is an innovative, customisable adaptive AI that has changed online, hybrid learning and teaching methods. It permits sharing of instructional materials, online tests, and other resources with students and lecturers in a setting that fosters interaction and collaboration. Personalised suggestions enabled by AI are one of its primary features. The program makes personalised recommendations to students based on their learning styles and interests using cutting-edge AI algorithms. The peer-to-peer learning capabilities of the platform are another crucial part. Thanks to it, students can interact with one another, join or start learning groups, and participate in group discussions. They can also collaborate and share resources to understand and remember the information. Students may access the platform on their mobile devices by downloading the mobile app. This mobility enables students to learn on the go and stay connected with their peers.

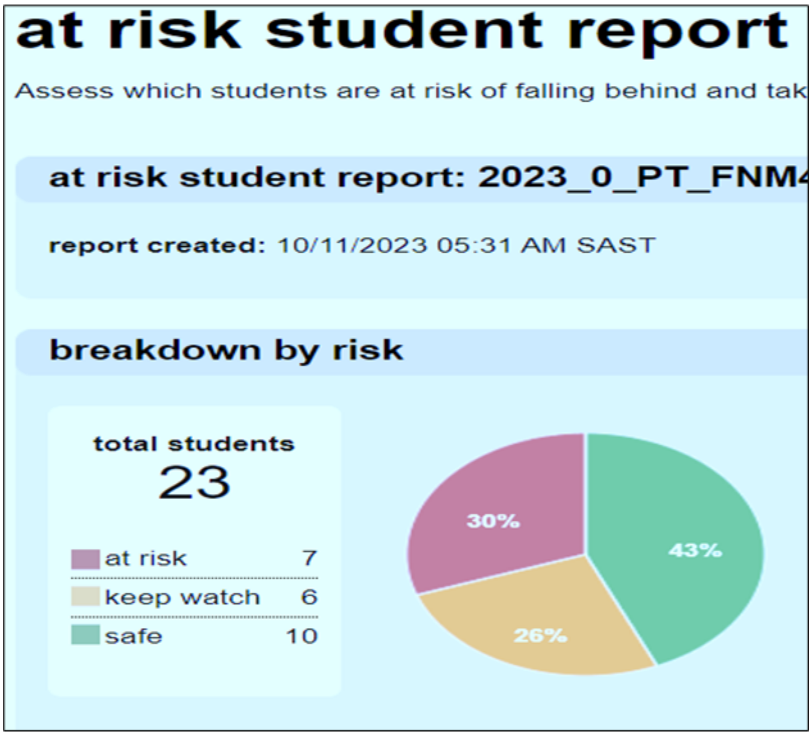


Figure 3-12 At-risk

Instructors supplied recommendations to facilitate self-paced learning, as most adaptive assignments involved individual learning activities. Instructors designed personalised learning paths to cater to students' unique learning goals and mastery levels. Before students addressed significant goals, instructors allotted ample time for them to learn and reflect.

Self-paced learning created the potential for students to procrastinate and fall behind, as depicted in Figure 3-12 and Appendix 6 (I), highlighting the at-risk students. Therefore, the instructor intervenes with cues and presents blended online personalised content, as illustrated in Figure 3-13, or in-person guidance sessions, as well as more time on significant assessments and rational opportunities for students to grasp the content. The instructor enhanced their comprehension of their student's progress by skilfully using the learning analytics provided by the adaptive system. Student-centred learning analytics, which includes the rate of knowledge acquisition, access frequency, time spent, student progress, and learning performance, supply valuable insights that help instructors check their students' progress.

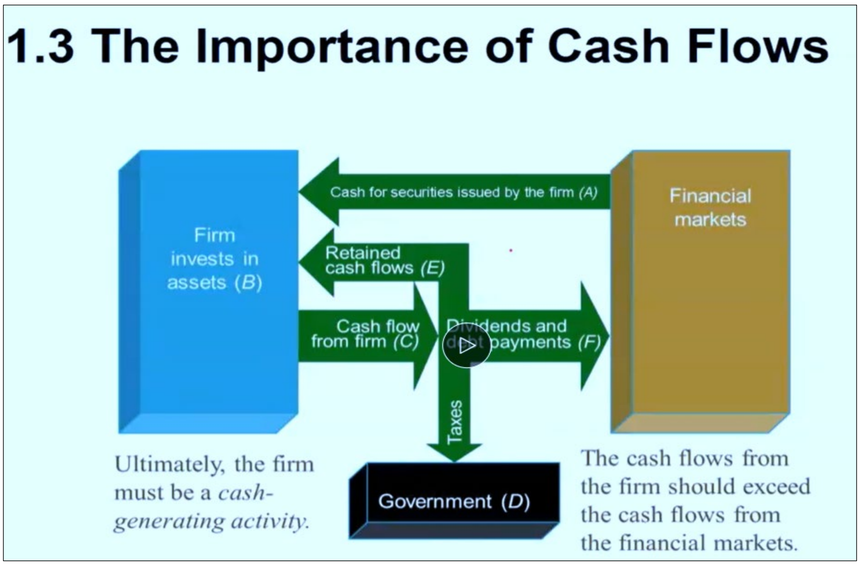


Figure 3-13 Blended lessons and recordings

An early progress feedback alert system is beneficial, as it enables students to remain focused on their tasks by prompting instructors to create automatic prompts based on inactivity or unusual learning tempos. Additionally, the instructor checks students procrastinating or engaging in potentially dishonest practices, as indicated earlier in Figure 3-12. As facilitators, instructors evaluate their students' progress and engage with them to find areas of learning gaps, misconceptions, and challenging concepts. Drawing from these dashboards' insights, the instructor organises additional in-class group discussions and group assignments, depicted in Figure 3-14, to offer supplementary help to groups of students grappling with similar difficulties. Appendix 6 (J) offers other examples of the work undertaken by lecturers. Instructors may provide personalised cumulative reviews to specific groups or individual students, helping them connect their embedded knowledge with new concepts. Programmed and instructor-led studies proved indispensable in elevating the adaptive learning process. In summary, the survey data assist in verifying the students' belief of the influence of the AI platform as a peer-to-peer support tool.

Figure 3-14 Additional group work

In the following quantitative data source section, I will transition to the quantitative data sources and student engagement. I will explore the influence of AI-driven platforms on engagement.

3.8.2 Engagement

This investigation will explore the outcomes of nineteen archival surveys, illustrated in Figure 3-15 and Appendix 4.

20/09/2023, 07:52 Financial Management September 2023

28. Do you believe AI can identify and address gaps in your understanding? *

Tick all that apply.

- [ ] Strongly Disagree
- [ ] Disagree
- [ ] Neutral
- [ ] Agree
- [ ] Strongly Agree
- [ ] Unable to answer

29. How would you rate the feedback quality from the AI system? *

Tick all that apply.

- [ ] Poor
- [ ] Below Average
- [ ] Neutral
- [ ] Good
- [ ] Excellent
- [ ] Unable to answer

Figure 3-15 Survey Question Example

The study assumes an objective reality despite the subjectivity of beliefs. Engagement, for instance, is gauged through student perception of the system, attendance, time-on-task, and qualitative sentiments. Differing metrics and indicators inform a multidimensional analysis of students' experiences with the AI-assisted platform. Appendix 6 (M) illustrates further examples. The survey reviews the students' beliefs and perceptions regarding the AI platform as a peer-to-peer support tool at the onset of the academic year.

When the semester starts, course educators supply explicit syllabus documentation that includes clear assignments, grading policies, and criteria for progressing into the next class, as illustrated in Appendix 6 (K).

3.8.2.1 Connect® and the Learner Management System

McGraw-Hill Higher Education (MGHE) has developed the AI platform, an adaptive learning system that comprises SmartBook and LearnSmart. The SmartBook is a digital textbook that covers topics the instructor chooses to supplement the course syllabus. LearnSmart is an online feature that delivers content to students in modules. The software uses a rating system to gauge students' confidence levels in answering content-related questions, which is then considered along with their earlier responses to select the following questions. However, impartial pragmatic evidence on the effectiveness of LearnSmart is limited, and outcomes from investigations have been varied (Dry, 2018). The adaptive learning system also checks the number of questions successfully answered and the confidence levels of student performance. It redirects them to the proper sections of the eBook (SmartBook) for concept revision upon incorrect responses. Students must reassess the information and correctly answer the questions to advance (Allison, 2017). A variety of features offered by Connect® and the learner management system look to give students a thorough learning and teaching experience. Its main characteristics include the following:

- The platform gives lecturers access to the platform's course creation and management tools. The ability to track student progress and add learning resources, exams, and assignments to a course is available to instructors.
- Students can interact and engage while improving their knowledge of the course material. The platform provides learners with immediate feedback on their performance.
- The lecturer regularly shares announcements and course content on the learner management system.

These features include communication, mobile compatibility, assessment, analytics, content development, personalisation, and integration with learner management practices.

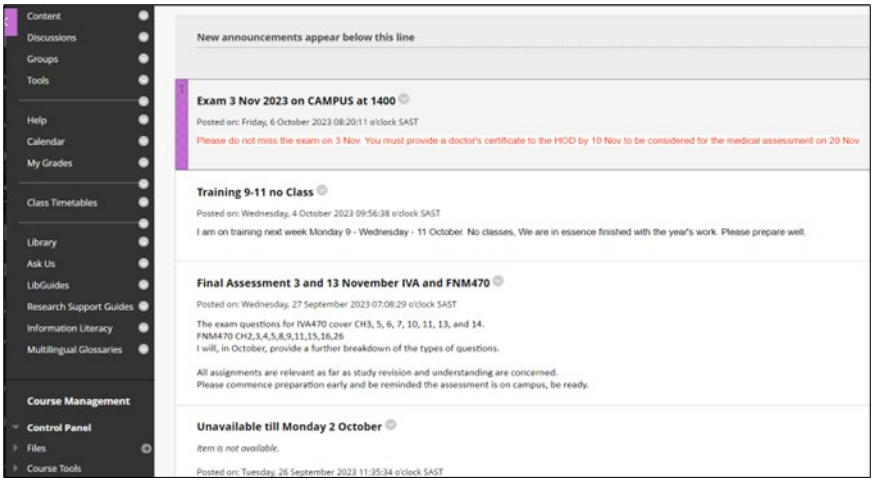


Figure 3-16 Announcements

Course management supplies the capability to create and oversee courses, set objectives, and allocate learning resources to students. This tool helps instructors seamlessly incorporate course materials such as videos, PDFs, and quizzes. Announcement tools, illustrated in Figure 3-16, discussion forums, and messaging enable effective communication between students and instructors. This feature allows learners to discuss and exchange ideas with each other, fostering a collaborative learning environment. Examinations, assignments, and quizzes are assessments facilitators may use and make available by the all-inclusive assessment system in Appendix 6 (G). The platform offers choices for tailoring the evaluation procedure and monitoring learner performance.

Analytics offers thorough analytics that lets lecturers monitor students' progress and evaluate their work, as illustrated in the at-risk report in Appendix 6 (I). The analytics dashboard provides methods to gauge student progress, as shown in Figure 3-17,

Assignments	Score	Started	Submitted	Time spent (HH:MM)	Date scored
CH1 Introduction to Corporate Finance Assignment 1 Total Value (Points): 100.00 , Average Score: 100.00 (100.00 %)					
Attempt 1	100.00(100.00%)	02/06/23 06:52PM SAST	02/06/23 11:08PM SAST	Not timed	02/06/23 11:08PM SAST
Introduction to Corporate Finance Assignment 2 Total Value (Points): 100.00 , Average Score: 45.33 (45.33 %)					
Attempt 1	64.00(64.00%)	02/13/23 02:23PM SAST	02/15/23 01:38PM SAST	2:29	
Attempt 2	72.00(72.00%)	02/15/23 01:46PM SAST	02/17/23 10:58AM SAST	1:21	
Attempt 3	0.00(0.00%)	02/17/23 03:21PM SAST	02/19/23 11:59PM SAST	0:00	
CH2 Cashflow and Statements Assignment 1 Total Value (Points): 100.00 , Average Score: 100.00 (100.00 %)					
Attempt 1	100.00(100.00%)	02/21/23 07:27PM SAST	02/25/23 01:00PM SAST	Not timed	02/25/23 01:00PM SAST
CH2 Cashflow and Statement Assignment 2 Total Value (Points): 100.00 , Average Score: 20.00 (20.00 %)					
Attempt 1	20.00(20.00%)	03/05/23 10:03PM SAST	03/05/23 11:59PM SAST	1:04	
CH2 Cash flow and Statements Assignment 3 Total Value (Points): 100.00 , Average Score: 31.01 (31.01 %)					
Attempt 1	65.17(65.17%)	03/06/23 11:59AM SAST	03/11/23 02:33PM SAST	3:28	
Attempt 2	27.86(27.86%)	03/12/23 04:17PM SAST	03/12/23 04:37PM SAST	0:19	
Attempt 3	0.00(0.00%)	03/12/23 04:38PM SAST	03/12/23 11:59PM SAST	0:00	
Class test Fin Mgt 4 17 March 2023 Total Value (Points): 80.00 , Average Score: 37.00 (46.25 %)					
Attempt 1	37.00(46.25%)	03/17/23 08:30AM SAST	03/17/23 09:57AM SAST	1:26	
CH3 Financial Statement Analysis Assignment 1 Total Value (Points): 100.00 , Average Score: 100.00 (100.00 %)					
Attempt 1	100.00(100.00%)	03/13/23 07:31PM SAST	03/14/23 07:08PM SAST	Not timed	03/14/23 07:08PM SAST
CH3 Financial Statement Analysis Assignment 2 Total Value (Points): 100.00 , Average Score: 34.00 (34.00 %)					

Figure 3-17 Student Progress

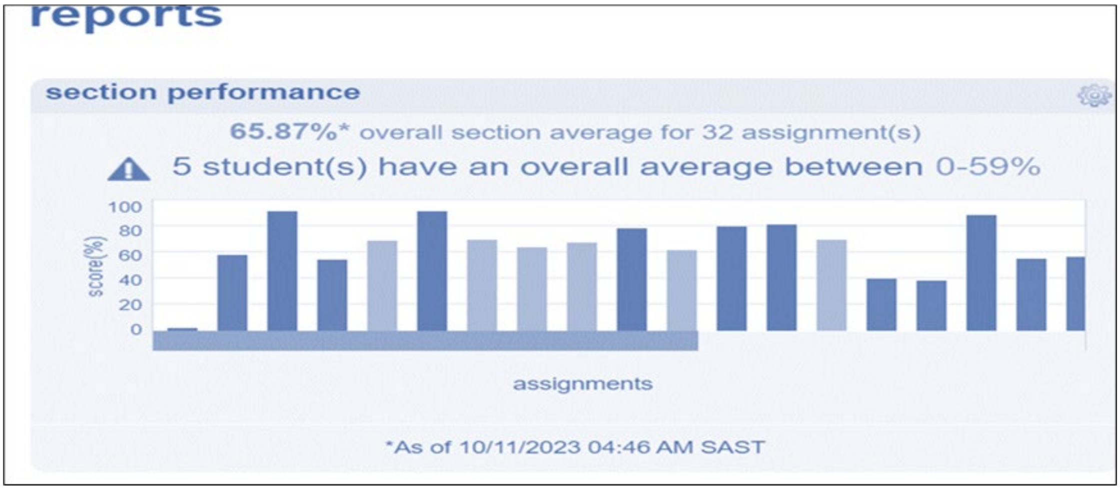


Figure 3-18 Performance Report

achievement levels in Figure 3-18, Engagement in Figure 3-19 represented by the scatter access graph compared with grades, and further examples in Appendix 6 (D) are integral to ascertaining the time spent on the platform. Importantly, this time does not reflect the amount of practice the students undertake on a particular task.

Learning is more comfortable and accessible thanks to mobile compatibility, which allows students to access course materials and complete assessments on their smartphones or tablets, impacting activity levels as illustrated in Figure 3-19. Personalising learner experiences and access to materials according to their interests and learning preferences helps them acquire related knowledge more effectively. With the help of an easy-to-use writing tool,

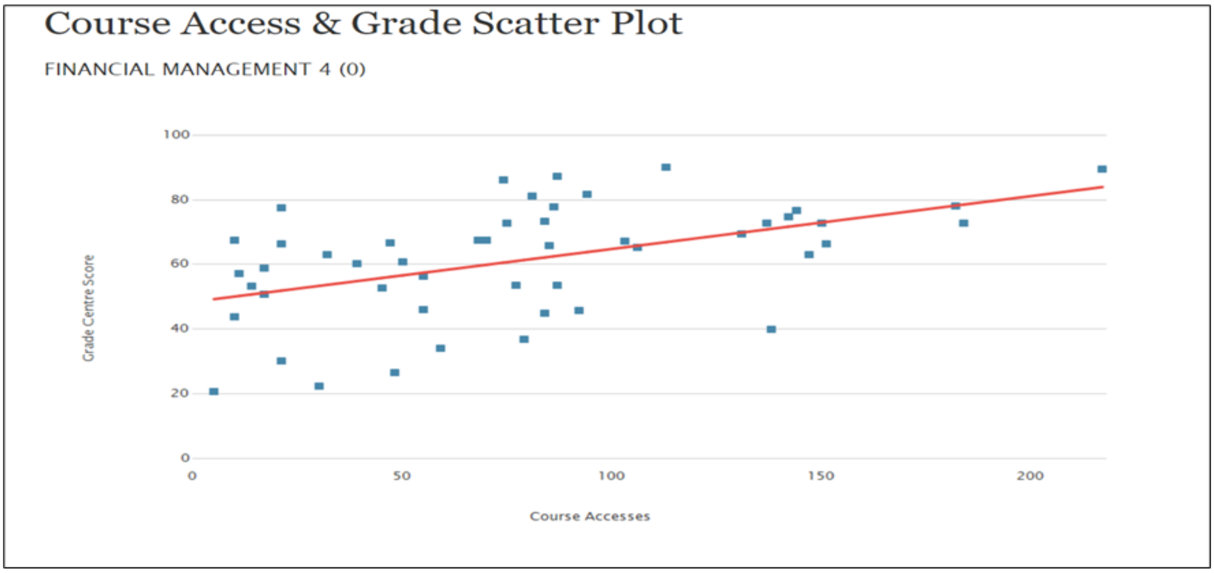


Figure 3-19 Scatter graph depicting engagement.

facilitators can create and publish their individualised content. Integrating AI-peer platforms like Open AI and GPT-4 enhances users' learning experiences. This AI-peer platform offers personalised integration and feedback based on student performance and learning preferences, influencing student performance and retention. Student perception of their grade performance is an added aspect of their experience and, as such, is analysed.

3.8.2.2 Lesson Objectives

The first step in designing an adaptive course is to define specific learning objectives and establish the boundaries for the various content (Willcox & Huang, 2017). Willcox & Huang (2017) created adaptive content, identifying small units of knowledge known as "Smart Book" or assignment lessons, each requiring around 30 minutes to complete. This process involves breaking down each learning objective into easily understood concepts, resulting in mini-lessons per course. Instead of delivering complete chapters, students are frequently evaluated after each lesson to measure mastery of one or more learning objectives, as illustrated in Appendix 6 (F). The approach to structuring content allows for a more tailored and adaptive learning experience Cavanagh et al. (2020), as described in Figure 3-20 and Appendix 6 (C), by categorising.

Expand each category to see scores.

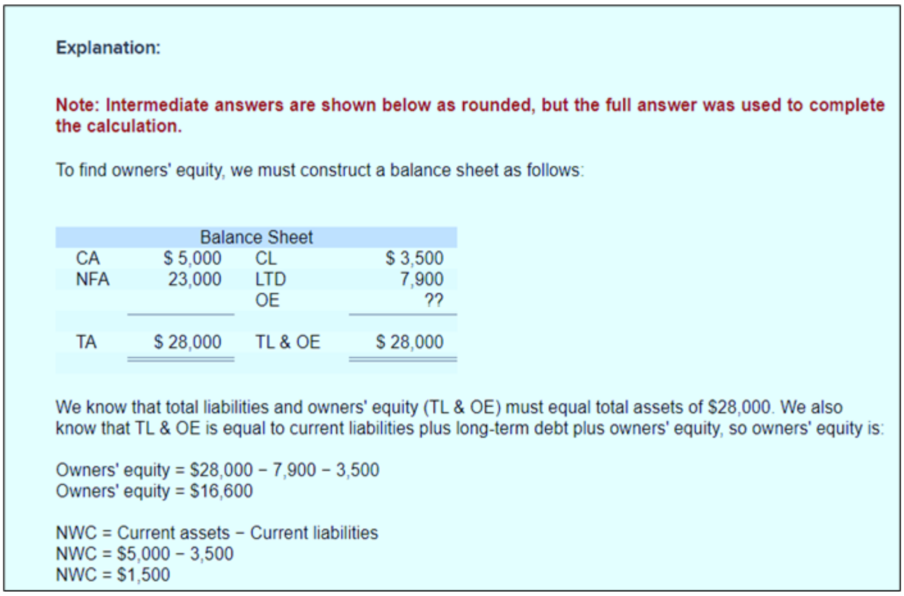
Section	Questions	Students submitted	Category score (Best assignment attempt)
1.1 What is Corporate Finance?	33	18/21	42.85%
1.2 The Corporate Firm	72	19/21	46.09%
1.3 The Importance of Cash Flows	21	19/21	52.00%
1.4 The Goal of Financial Management	18	18/21	38.65%
1.5 The Agency Problem and Control of the Corporation	33	19/21	44.07%
1.6 Regulation	14	10/21	34.52%
11.2 Expected Return, Variance, and Covariance	7	0/21	0.00%
11.3 The Return and Risk for Portfolios	9	0/21	0.00%
11.7 Riskless Borrowing and Lending	2	0/21	0.00%
11.8 Market Equilibrium	5	0/21	0.00%
11.9 Relationship between Risk and Expected Return (CAPM)	10	0/21	0.00%
15.1 Some Features of Common and Preferred Stocks	14	0/21	0.00%

Figure 3-20 Lessons associated with the objectives.

The method splits learning objectives into smaller concepts, facilitating mini-lessons. Evaluations occur after each lesson, measuring mastery over dreams. This structure paves the way for exploring individual content and theory for more targeted learning. In creating adaptive courseware, lecturers break down learning objectives into smaller units of information or skills. Subsequently, lecturers produce materials for content, assessments, and feedback. Adaptive systems heavily rely on evaluations to personalise instruction to attain the unique requisites of each student (Cavanagh et al., 2020). Assignments, quizzes, homework, and graded assessments achieve this accomplishment.

Unlike traditional online courses, instructors dedicate more time to creating judgments and reactions than creating matter. While developing the adaptive systems, instructors identify gaps in the question pool and strive to include more questions in each lesson, as a higher number of questions leads to a more comprehensive learning experience. For example, completed adaptive courses expand their question pool to over 1,000, as opposed to a couple previously used for each chapter, as illustrated in Appendix 6 (G).

Detailed feedback is vital to the adaptive course design (Mandouit & Hattie, 2023). Through continuous practice and feedback, students can improve their performance, recognise areas that require improvement, and receive assistance and direction to develop their skills (Hizli, 2023). Instructors must provide detailed advice during the assignment question phase to expedite student knowledge development (Schellens & Valcke, 2006). This could include referring to the preferred answer, the rationale for a particular response, or suggestions for students to search specific topics. In the platform, as shown in Figure 3-21, presenting questions from Connect® with detailed feedback enhances student learning, further evidenced in Appendix 6 (E).


Explanation:

Note: Intermediate answers are shown below as rounded, but the full answer was used to complete the calculation.

To find owners' equity, we must construct a balance sheet as follows:

Balance Sheet			
CA	$ 5,000	CL	$ 3,500
NFA	23,000	LTD	7,900
		OE	??
TA	$ 28,000	TL & OE	$ 28,000

We know that total liabilities and owners' equity (TL & OE) must equal total assets of $28,000. We also know that TL & OE is equal to current liabilities plus long-term debt plus owners' equity, so owners' equity is:

Owners' equity = $28,000 − 7,900 − 3,500
Owners' equity = $16,600

NWC = Current assets − Current liabilities
NWC = $5,000 − 3,500
NWC = $1,500

Figure 3-21 Illustration of feedback on each question.

Creating various learning activities to meet each student's unique learning needs is challenging for instructors, facilitators, and instructional designers, as highlighted by (Khosravi et al., 2020). Designing and developing such activities is time-consuming and needs to be addressed in the literature (Essa, 2016; Baker, 2016). Pavlik Jr et al. (2013) estimated that it required 200 hours of content creation development for every period of subject design. Similarly, Aleven et al. (2009) found that an instructor alone needed 25 hours to create one hour of content using intelligent tools. Due to limited resources, faculty members collaborated with moderators to concentrate on developing one or two adaptive modules per semester, resulting in prolonged completion time for a single adaptive course illustrated in Figure 3-22. Faculty members often collaborate with moderators to focus on a limited number of adaptive modules per semester, elongating the time needed for course completion.

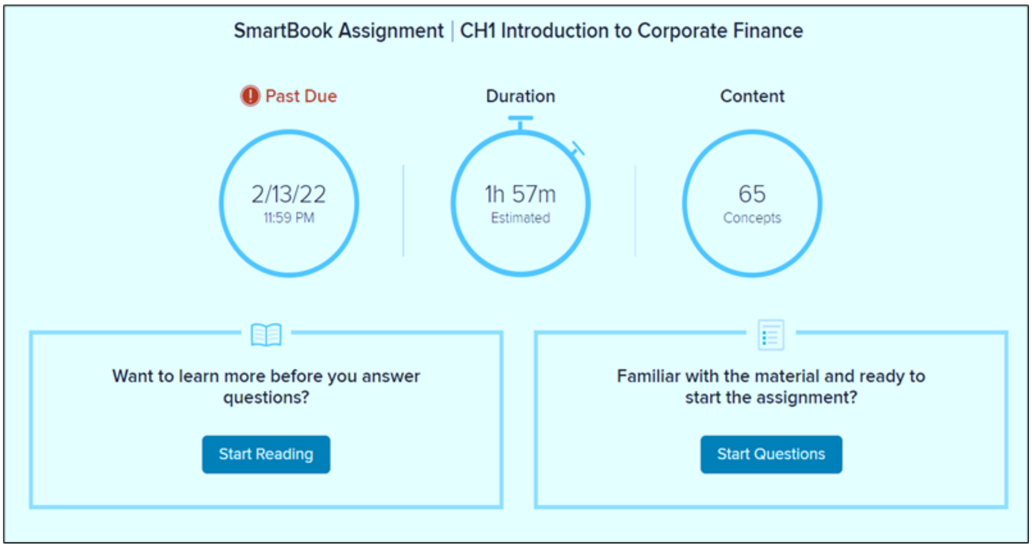


Figure 3-22 Creating an Adaptive Course

In summary, the functionality of the AI platform influences students' perception of their overall performance, which determines their satisfaction with learning. The elongation sets the stage for discussing adaptive personal knowledge acquisition or peer-to-peer, a potential solution for enhancing the efficiency and efficacy of content development for learning.

3.8.3 Grades and Pass Rates

The study accessed course grade and pass rate data, pre-and post-implementation of the AI-assisted learning platform. The courses include Financial Management 1, 2, 3, and 4 for 2017-2022. Figure 3-23 illustrates an extract of the grades database from one subject, Financial Management, for 2022. Appendix 6 (X) shows additional raw data.

Cape Peninsula University of Technology

Pass Rates and Average Final Marks

Report Parameters	
Year	2022
Department	MANAGEMENT & PROJECT MGNT

Department	Period Of Study	Module	2022 Enrolments	Passed	Pass Rate	Average Final Mark
BUSINESS & MANAGEMENT SCIENCES						
MANAGEMENT & PROJECT MGNT	4	Purposely Blanked				
		FINANCIAL MANAGEMENT 4 (FNM470S)	76	63	82,9%	57
		Purposely Blanked				
		Purposely Blanked				
		Purposely Blanked				
		Purposely Blanked				
		4 TOTAL	375	261	69,6%	52
	MANAGEMENT & PROJECT MGNT TOTAL		**375**	**261**	**69,6%**	**52**
BUSINESS & MANAGEMENT SCIENCES TOTAL			**375**	**261**	**69,6%**	**52**
Report Total			**375**	**261**	**69,6%**	**52**

Report Definitions	
At risk modules	Modules with a pass rate that is less than the set target in the University enrolment plan of 79%
High impact modules	Modules with enrolments numbers above 100 and with a pass rate below 79% and/or average final mark less than 50%
On pass rates	
Green	Modules with a pass rate that is equals to or greater than 79%. These modules have met the national benchmark for pass rates
Yellow	Modules with a pass rate that is between 50% and 78.99%
Red	Modules with a pass rate below 49.99%. These modules sit far below the national benchmark.
On average final mark	
Red	Modules with an average pass mark below 50%

Figure 3-23 Pass Rates and Grades Financial Management 4

Developing content and assessments for adaptive learning can be challenging and time-consuming. However, the potential benefits to grades include creating a personalised and evolving learning experience. A significant influence on grade performance is the functionality of randomising assessment questions.

One way to enhance this adaptive experience is using content variables, groupings, and conditions. For example, various financial algorithmic variables in the design were incorporated depending on a student's major, ensuring each learner receives relevant content. The course coordinator applied these variables to the course's quantitative components. These features include random number generation for practice problems and assessments using Microsoft Excel. Grouping and conditions can also manifest specific question groupings based on predefined circumstances. These circumstances could be related to problem variables or specific values within learning content, allowing the content to appear only under numerical conditions. For instance, Figure 3-24 displays an assignment with entrenched randomised variables from a course, where each student received a case study with the interaction and feedback. This design motivated students to practice the choice repeatedly since a different assignment was presented for each challenge, as depicted in Appendix 6 (E).

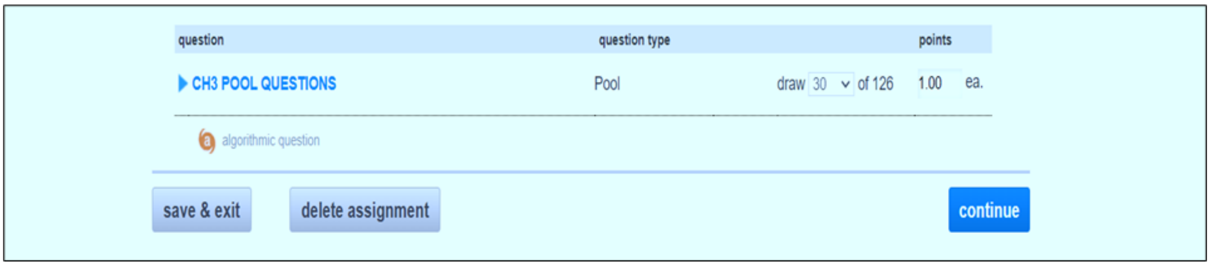


Figure 3-24 Algorithmic and Randomised Options

There are techniques to arrange the five adaptive design features in a pool question in Figure 3-25, depending on the available content and the ability of the subject matter expert or instructor illustrated in Appendix 6 (Q). This collaboration develops new and innovative adaptive learning solutions that are more effective in meeting learners' needs and the lecturer's role.

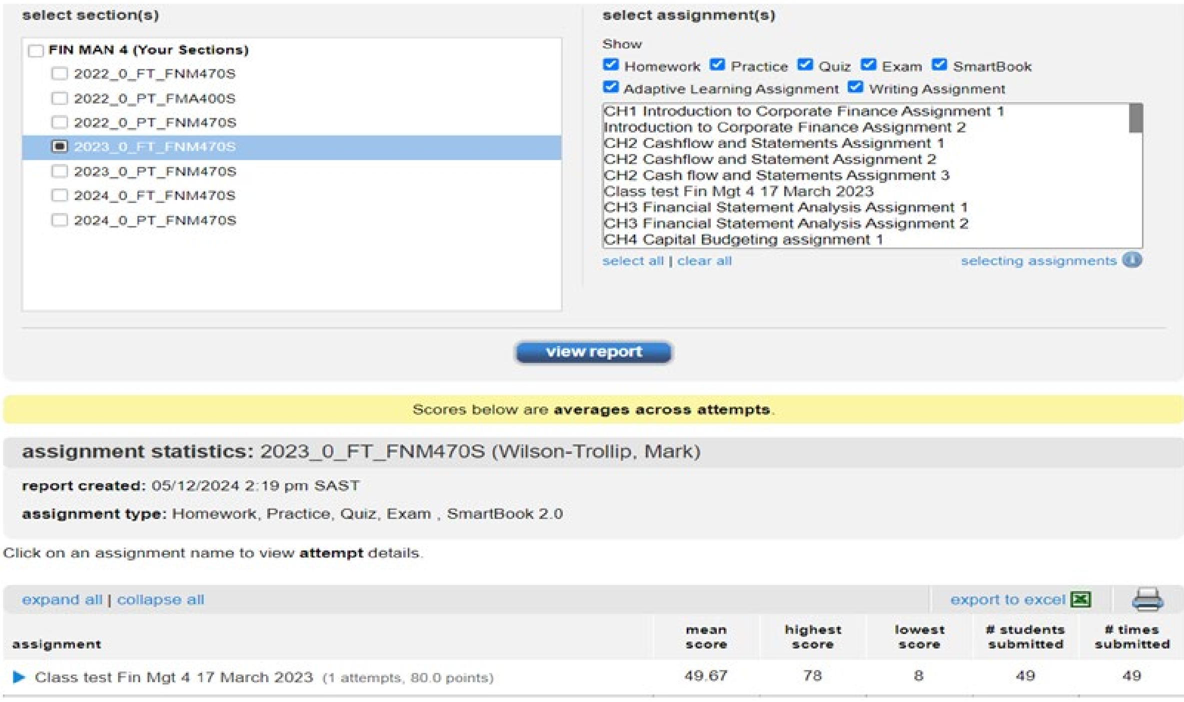


Figure 3-25 Assignment and Assessment Statistics

Additional sources were extracted for analysis, as illustrated in Figure 3-26 Assignment and Assessment Statistics.

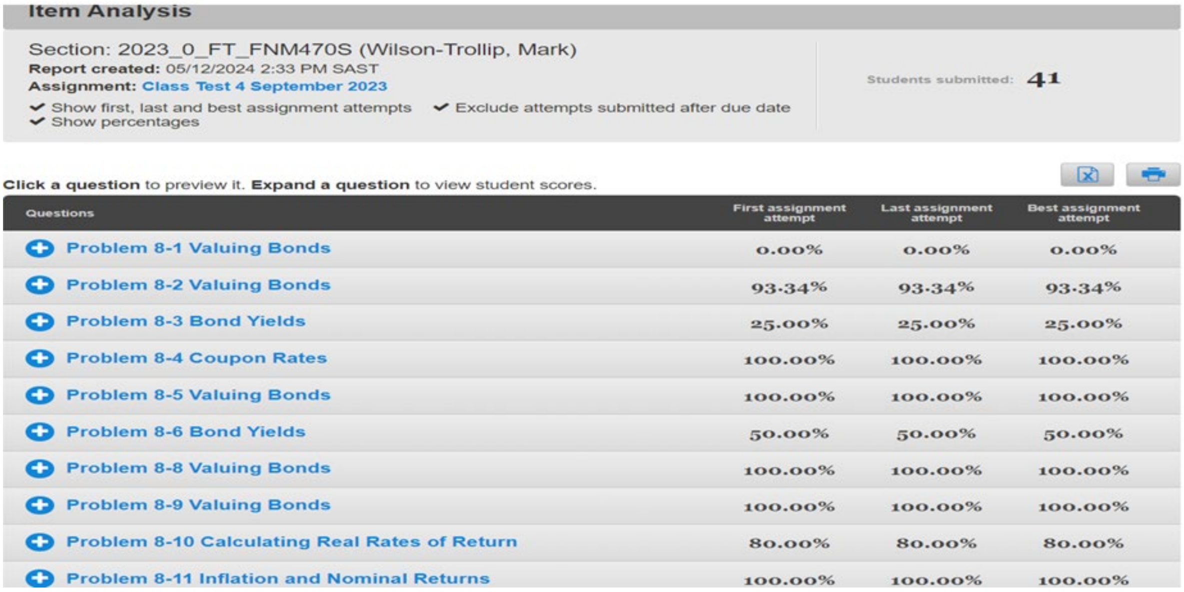


Figure 3-26 Item Analysis

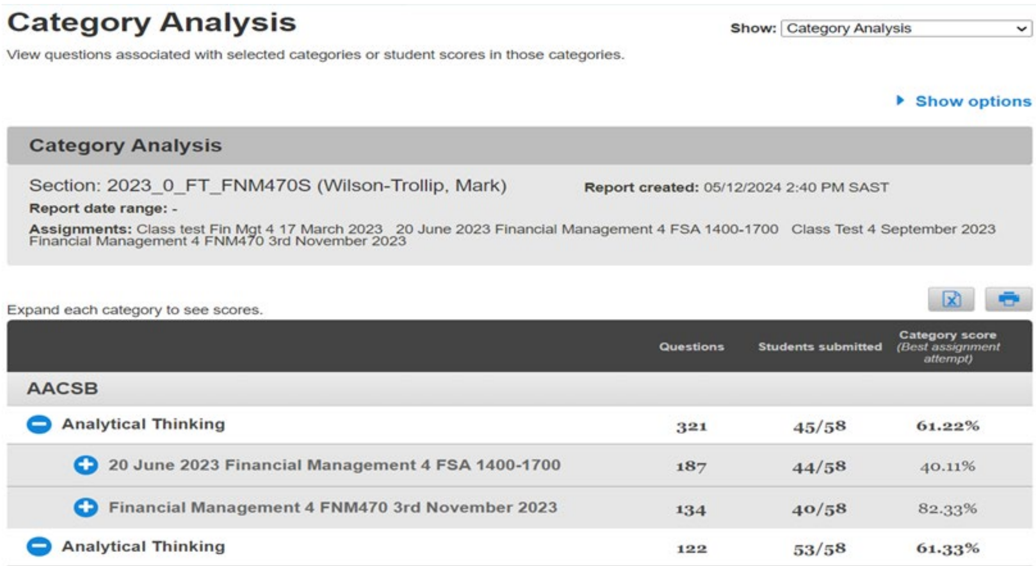


Figure 3-27 Category Analysis

Similarly, analysing data by question type identifies focus areas for lecturers, one of which is analytical thinking. It is available per-student basis, thus meeting one of the requirements for peer-to-peer support, illustrated in Figure 3-27 Item Analysis. Further category analysis supports the discussion section where the importance of Figure 2-19 Bloom's: The Flourishing

Academic (Bloom, 1984) (Bloom, 1984; Tinto, 2017; Bean & Metzner, 1985) prevails. Following the data sources, the study pivots to the data analysis.

3.9 Data Analysis

Yin (2009: 109) defines data analysis as "consists of examining, categorising, tabulating, testing, or otherwise recombining both quantitative and qualitative evidence to address the initial propositions of a study". This study captures the essence of validity and reliability while addressing the analytical procedures (Yin, 2009). Hence, data triangulation supports validating "Are we developing the interpretations we want? (Stake, 1995: 107).

Thematic analysis (TA) approaches capture semantic (explicit or overt) and latent (implicit or underlying) meanings. These approaches detail the processes of coding and theme development. Additionally, they allow for flexibility in the theory that frames the research. According to Braun & Clarke (2019), there are three broad types of TA: Coding reliability, Reflexive approaches and Codebook approaches. This study uses the reflexive approach, although it does not discuss the different types of TA. It involves "themes developed from codes and conceptualised as patterns", "Themes cannot exist separately from the researcher—the researcher generates them through data engagement mediated by all that they bring to this process (e.g., their research values, skills, experience and training)" (Braun & Clarke, 2021: 39).

Table 3-5 Statistical Methods

Statistical Tests and Analysis	Objective	Research Questions Affected by Analysis
Reflective Thematic Analysis	To facilitate the making of informed and reflexive analytic choices. This approach helps in understanding the implications and possibilities enabled by these choices.	How do AI-assisted platform features relate to academic achievement? What factors determine an AI platform's influence on students' engagement perceptions?
Descriptive Factor Analysis	To summarise and interpret the data collected on learners' beliefs and experiences with the platform.	
Correlation Matrix	To provide valuable insights into the relationships between the variables.	

Statistical Tests and Analysis	Objective	Research Questions Affected by Analysis
The Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test of Sphericity	The Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test of Sphericity provide vital insights for AI and peer-to-peer.	How do students perceive the effectiveness of peer-to-peer support in AI platforms?
Total Variances	It shows how much of the overall variability in the data can be explained by the factors identified in the analysis.	
Commonalities	Commonalities indicate how much of the variance in each variable is accounted for by the factors extracted in my factor analysis, showing how well the factors represent each variable.	
Component Matrix	This matrix shows how each variable (question from my survey) relates to the identified factor(s).	
Descriptive two-tailed t-tests for grades and pass rates	To compare the means of the collections and evaluate significant differences in academic performance between learners who used the AI-Peer platform and those who did not.	

The study conducts reflexive analysis, factoring, and statistical t-tests to comprehensively analyse the data, as illustrated in Table 3-5. By applying these statistical methods, the study aims to provide insights into how optimising the design and implementation of AI-peer platforms can enhance their effectiveness in improving learner performance using statistical tools, as seen in Appendix 6 (R). The study includes reflexive thematic analysis, factor analysis and t-test statistical analysis. The former two address engagement, and the latter deals with performance. Let's extend the reflection to encompass all the educational theories mentioned previously—Humanistic, Cognitive Load, Socio-economic, Constructivist, and Personalised Learning. These theories are significant constructs in the Retention Theory and the Theory of Attrition (Tinto, 1975; Bean, 1988).

The analysis extends to three themes of the study: engagement, performance and peer-to-peer. This approach will examine the influence of my biases and assumptions on interpreting data from these different theoretical perspectives, recognising how these influences affect the analysis of specific questions linked to each theory. The survey design linked each question to a theoretical framework, ensuring relevance and alignment. The questions were assigned varying weights based on their importance within the theories. The importance weightings of each question in the constructs are Essential, Important, Considerable, and Minor.

Factoria is applied to the survey questions using the Likeart system and analysed statistically, illustrated in Appendix 4. Finally, the grade performance data is analysed using t-tests.

This methodological approach helps prioritise aspects of the examined theories, such as humanistic, cognitive load, socio-economic, and constructivist, enhancing the analytical precision of the survey results.

3.9.1 Humanistic Theory

“To help teachers foster a climate of trust in the classroom so that curiosity and the natural desire to learn can be nourished and enhanced; to encourage a participatory mode of decision making in all aspects of learning, a role in which students, teachers, and administrators each have a part; to help students prize themselves, to build their confidence and self-esteem; to uncover the excitement in intellectual and emotional discovery, which leads students to become lifelong learners; to develop in teachers the attitudes that research has shown to be most effective in facilitating learning; to help teachers grow as persons and find rich satisfaction in their interaction with learners; to provide a support group for educators through contacts with networks, organisations, and individuals who are concerned about person-centred learning; to provide a resource guide of books, materials, and publications that will extend and generate new ideas [and] to create an awareness that for all of us, the good life is within, not something that is dependent on outside sources” (Rogers & Freiberg, 1994: Abstract).

Question Example: "The lecturer stimulated my interest in the course topic?"

Reflexive Consideration: My educational philosophy may inherently value personal engagement and emotional connection in the learning process, influencing how I interpret the importance of student interest, i.e., setting the mood (Rogers & Freiberg, 1994).

3.9.2 Cognitive Load Theory

Effective cognitive load management aims to optimise learning by balancing student demands. This management involves designing educational activities that enhance comprehension and retention while preventing cognitive overload. The goal is to ensure that the cognitive resources required do not exceed the learner's capacity, facilitating more efficient learning experiences. The theory addresses artificial learning and problem-solving difficulties that instructional design can manipulate. Intrinsic cognitive load is considered a fixed aspect of learning material, inherent due to the complexity and interactivity of its elements. This type of cognitive load is determined by the nature of the content itself, unlike artificial difficulties imposed externally. It does not change across different instructional conditions for the same material. Most schemas require simultaneous learning of interacting elements needed to understand these schemes. In areas with multiple interacting elements, intrinsic cognitive load is high.

Conversely, where elements do not interact, they can be learned successively, resulting in a low intrinsic cognitive load. The theory also suggests that extraneous cognitive load, which hinders learning, only poses a problem in high cognitive load conditions caused by high element interactivity. Reducing extraneous cognitive load may not yield significant results in low interactivity scenarios. Additionally, element interactivity helps explain the difficulty in learning and understanding certain materials, mainly when the material involves high element interactivity and inherently high cognitive load (Sweller, 1994).

Question Example: "The lecturer explains concepts clearly."

Reflexive Consideration: An academic and business background emphasising clarity and simplicity in teaching may influence my interpretation. There's a risk of assuming that clarity directly correlates with reduced cognitive load without considering that different students have varied capacities and learning styles that might affect their perception of clarity.

3.9.3 Socio-economic Theory

Examines how social and economic factors influence educational access and success. (Scoble et al., 2010: Abstract) “Suggests that the concept of institutional research capital be expanded to include the capture and evaluation of socio-economic impact. The Socio-economic theory argues that understanding the typology of impacts and the tracking will assist in formulating institutional strategies for capturing socio-economic impact”.

Question Example: "Would you prefer to pay R1500 for a textbook or R500 for Connect and its resources?"

Reflexive Consideration: It is crucial to recognise my socioeconomic background and how it may colour my perceptions of financial barriers in education. This awareness helps assess whether I overvalue or undervalue the impact of economic factors on educational access and success.

3.9.4 Constructivist Theory

“The epistemic assumptions of constructive learning are different from those of traditional instruction, so classical needs and task analysis methods are inappropriate for designing constructivist learning environments (CLEs). Since conscious learning emerges from activity (performance), not as a precursor to it, CLEs should attempt to replicate the activity structures, tools and sign systems, socio-cultural rules, and community expectations that performers must accommodate while acting on some object of learning” (Jonassen & Rohrer-Murphy, 1999: Abstract).

Question Example: "The lecturer challenges me to think independently?"

Reflexive Consideration: Given my favourable view of constructivist approaches, there is a tendency to positively bias interpretations toward pedagogies that promote active learning and independence. Reflecting on this bias ensures I don't overlook this approach's potential challenges and limitations for students who may benefit from more structured or guided learning experiences.

3.9.5 Personalised Learning Theory

Emphasises customising the learning experience to fit individual needs and preferences. “Personalised learning (PL) is learning in which the stage of learning and the instructional approach are optimised for the needs of each learner. The concept of PL allows e-learning design to shift from a ‘one size fits all’ approach to an adaptive and student-centred approach” (Fariani et al., 2023: Abstract).

Question Example: "This course adds value to my qualifications."

Reflexive Consideration: My enthusiasm for customised learning experiences might lead me to assume that all students perceive personalised learning as beneficial, potentially skewing my interpretation of their responses. It’s necessary to reflect on how different student preferences might influence their perception of the course's value.

After explaining the theories and their correlation to the survey questions, allocating weight to the importance of the question in the respective theories becomes significant. These weightings and their descriptions are ranked adapted from the technique known as the discrimination value analysis technique (Salton et al., 1975), as illustrated in Table 3-3.

3.9.6 Weighting and Theme

Table 3-6 and Table 3-7 illustrate different examples of the qualitative archival survey questions by type, category, and weighting.

Table 3-6 Example of Archival Qualitative Questions by Type and Category

Type	Category	Questions
Closed Qualitative	AI Platform	Do you believe Connect offers better access to resources than a prescribed textbook?
Open Qualitative	AI Platform	Does Connect® support your learning?
Closed Qualitative	General	Do you understand the lecturer when he is presenting the course material?
Open Qualitative	General	If you have yet to attend online classes, why not?
Closed Qualitative	AI Platform	Is Connect easy to use?
Open Qualitative	AI Platform	Is the interactiveness of the assignments beneficial to students for embedded knowledge?
Closed Qualitative	General	The lecturer returns marked assessment tasks promptly.

Table 3-7 Weightings

Weighting	Description	Prioritising the weighting in terms of Importance in the Theory
Essential	Something essential is extremely important or necessary to a particular subject, situation, or activity. https://www.collinsdictionary.com/dictionary/english/essential "Essential learning outcomes mean state of knowledge, skills, attitude, and experiences of students in the following aspects: civic engagement, intellectual abilities, communication and interpersonal relations, which were resulted from several courses taught in senior high schools" (Kleebbua & Siriparp, 2016: Abstract)	(400) These would be terms whose presence most distinctly separates educational documents related to learning outcomes from others. These terms define the core content of a course (Salton et al., 1975).
Important	Something important is very significant, is highly valued, or is necessary. https://www.collinsdictionary.com/dictionary/english/important Factors that significantly affect the quality of the educational experience may not be as pivotal as essential factors.	(300) These terms are also practical in distinguishing themes but are secondary to essential terms
Considerable	Considerable, great in amount or degree. https://www.collinsdictionary.com/dictionary/english/considerable Elements that influence student satisfaction or course functionality but are less central to the core educational objectives.	(200) These terms contribute to theme distinction but are less significant than essential and vital terms.
Minor	Lesser or secondary in amount, extent, importance, or degree. https://www.collinsdictionary.com/dictionary/english/minor Peripheral aspects have minimal impact on the overall educational effectiveness but might affect specific students or situations.	(100) These terms have the most negligible discrimination value, indicating minimal impact on distinguishing between significant themes.

Table 3-8 shows the connection between each survey question and theories related to the Theory of Retention (Tinto, 1975) or the Theory of Attrition Theory (Bean, 1980). Emergent themes come from Tinto's Retention Theory and Bean's Attrition Theory. The questions are weighted, critical, high, moderate, and low regarding their importance to the theory (Braun & Clarke, 2021). Responses are coded as Essential: aspects that are essential for the course's success and directly impact student learning outcomes; Important: important factors that significantly affect the quality of the educational experience but may not be as pivotal as critical factors; Considerable: elements that influence student satisfaction or course functionality but are less central to the core educational objectives, Minor: Peripheral aspects that have minimal impact on the overall educational effectiveness but might affect specific students or situations. Finally, each question is further theme-coded: Engagement is the extent of student participation and interest in the course material. It includes factors like how often students contribute to class discussions, their enthusiasm for assignments, and their overall involvement in course activities. Performance pertains to the measurement of student success through assessments and outcomes. This measurement includes how students perform on exams, quizzes, and assignments, as well as the overall effectiveness of the course structure in promoting student achievement. Peer-to-Peer focuses on the interactions between students. It emphasises the importance of collaborative learning and group activities in enhancing the educational experience. This learning includes how students work together, share knowledge, and support each other's learning processes (Braun & Clarke, 2006). These contextual themes and factors are considered generic for this study. "Individualisation is a key component of successful support – students' perceptions that the assistance meets their specific needs increases student satisfaction and consequently retention" (Coates & Ransom, 2011: Abstract).

Table 3-8 Questions, Theories and Themes

Weighting	Question	Theory	Theme
Considerable	If you have not attended online classes, why not?	Theory of Retention	Engagement
Essential	Is Connect easy to use?	Cognitive Load Theory	Engagement
Essential	The lecturer clearly explained how weightings would be assessed.	Humanistic Theory	Engagement

Weighting	Question	Theory	Theme
Considerable	Does using the SmartBook direct you to the answers when doing assignments?	Cognitive Load Theory	Engagement
Important	Should the Connect system be used as part of the lecturers' toolkit?	Personalised Load Theory	Peer-to-Peer
Essential	Would you recommend Connect to other Universities?	Personalised Load Theory	Peer-to-Peer
Important	The assessment for this course was fair.	Theory of Attrition	Performance
Minor	Overall, this is a good course.	Theory of Attrition	Performance

To effectively code these questions thematically, as illustrated in Appendix 6 (GG), one can categorise them under the three themes based on their content and focus: Peer-to-Peer, Engagement and Grades and Pass Rates.

3.9.6.1 Peer-to-Peer: Reflexive Analysis

Peer-to-peer relates to student interactions within the course context, including collaborative learning, discussions, group projects, and other forms of peer engagement. This theme might involve aspects in the questions like:

- Collaboration and Interaction: Evaluate the opportunities for and effectiveness of student interactions, which are crucial for learning from peers and enhancing understanding through discussion.
- Support for Group Work: Feedback on the tools and structures that facilitate or hinder collaborative learning environments.
- Peer Learning Opportunities: The course design either fosters or inhibits peer-to-peer learning, and this research explores whether students perceive these interactions as valuable.

The research process gains depth and becomes more ethically and methodologically robust by applying reflexive analysis across all these theories. Factoria is applied to the same replies to data, offering additional rigour to the findings.

3.9.6.2 Engagement: Reflexive Analysis

The analysis of engagement focuses on the student belief system, the platform's engagement level, and its validity and rigour. Through reflexive analysis, I engage with the following practices to support the allocation of the theories and their weightings:

- Continuous Self-Questioning: I regularly question my assumptions and potential biases when interpreting data.
- Diverse Perspectives: I actively seek and incorporate diverse student perspectives to ensure an inclusive understanding of the data.
- Theoretical Flexibility: Maintaining flexibility in applying theoretical frameworks allows for integrating multiple theories to provide a more balanced view.
- Transparency and Openness: Being transparent about the influences on my analysis and open to alternative interpretations and critiques from peers.

3.9.6.3 Engagement: Factor

As illustrated in Table 3-9, I applied statistical factor analysis and Likert scales to the archival survey, data for rigour and validation, quantitatively assessing the platform's engagement effectiveness (Norman, 2010)[14] , also shown in Appendix 6 (R). Although qualitative by nature, O'Brien & Toms (2010) used Exploratory Factor Analysis to measure user engagement and quantitatively identify attributes of engagement, such as usability, felt involvement, and individual attention. Reliability Analysis, through measures like Cronbach's alpha, is used to assess the internal consistency of a survey instrument. This measure ensures that various items on a Likert scale, intended to measure specific constructs like usability and felt

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14 "Reviewers of research reports frequently criticize the choice of statistical methods. While some of these criticisms are well-founded, frequently the use of various parametric methods such as analysis of variance, regression, correlation are faulted because: (a) the sample size is too small, (b) the data may not be normally distributed, or (c) The data are from Likert scales, which are ordinal, so parametric statistics cannot be used. In this paper, I dissect these arguments, and show that many studies, dating back to the 1930s consistently show that parametric statistics are robust with respect to violations of these assumptions. Hence, challenges like those above are unfounded, and parametric methods can be utilized without concern for "getting the wrong answer"(Norman, 2010: Abstract).

involvement, are consistently interpreted by different users, maintaining the qualitative essence. This blending of methodologies allows you to preserve the qualitative nature of the constructs while providing a quantitative measure of their impact and relevance (O'Brien & Toms, 2010).

Table 3-9 Factoring Statistical Methods

Statistical Method	Description
Correlation Mix	This statistical test displays the strength and direction of relationships between variables. Each cell in the matrix shows the correlation coefficient between two variables, indicating how closely changes in one variable are associated with changes in another.
KMO and Bartlett's test	The Kaiser-Meyer-Olkin (KMO) test measures data adequacy for factor analysis. It checks the proportion of variance among variables that might be common variance. Higher KMO values (closer to 1.0) indicate appropriate factor analysis. Bartlett's Test of Sphericity tests the hypothesis that the correlation matrix is an identity matrix, which would suggest that variables are unrelated and unsuitable for factor analysis.
Commonalities	In factor analysis, commonalities are the part of the variance in each variable that is accounted for by the common factors. A higher commonality indicates that the variable correlates firmly with the other considered variables, suggesting it shares much common variance.
Total Variances	This test summarises the proportion of total variance in the data captured by each principal component when performing the principal component analysis (PCA).
Component Mix	In factor analysis, the component matrix displays each variable's coefficients (loadings) on each factor. These loadings measure how strongly each variable is associated with each factor, indicating how much of the variance in the variable is explained by the factor.
Rotated Matrix	This matrix results from applying a rotation technique to the factor analysis component matrix to achieve a more straightforward and interpretable structure. Rotation can make the output easier to understand by maximising the loadings of variables on one of the components while minimising their loadings on others. This process helps identify which variables are strongly associated with which factors, enhancing their interpretability.

Organisational, Psychological, Economic, Social and Environmental constructs, linked to Tinto (1975) & Bean (1988), guide the coding used in the factoring methods shown in Table 3-9. A review of instruments measuring learner satisfaction with virtual learning environments found that the past learner satisfaction questionnaires (LSQ) developed to measure learner satisfaction with the platform, validated by factor analysis, were most suitable for adaptation (Lim et al., 2022). Table 3-10 categorises the survey questions connected to the frameworks.

These frameworks consist of multiple components or constructs related to each other, as shown in Appendix 6 (S). They measure various aspects of learner commitment and accomplishment of the platform (Bohrnstedt & Marwell, 1978; Bacharach, 1989).

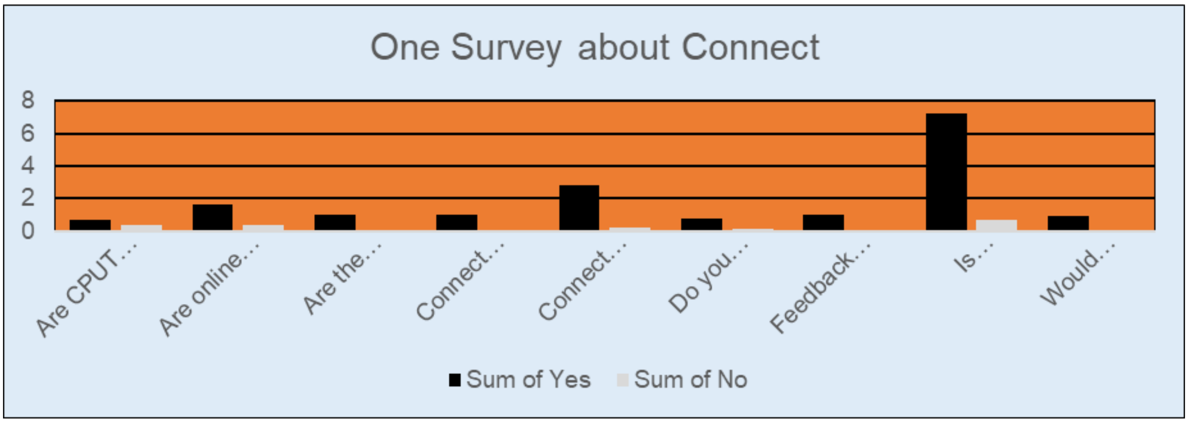

Figure 3-28 Examples of survey questions

Previous studies have successfully employed similar methodologies. For instance, studies in psychology and education often use coding to categorise open-ended responses and apply factor analysis to understand the dimensions of responses (Braun & Clarke, 2006). There is a theoretical basis for using such a methodology. For example, the Grounded Theory approach often uses coding to generate theories from data, and factor analysis can further assess these emergent theories (Glaser & Strauss, 2017).

The study aims to shape the content of the experience by providing categories and enhancing theories that define what is of interest[15]. Hence, using archival questions as a starting point considers what the aggregate data may imply about collective student beliefs, social contexts, and belief systems as a peer-to-peer support facilitator.

15 “Qualitative inquiry is not the property of any one discipline” (Eisner, 2017: 28).

The theory incorporates psychological, organisational, social integration, academic achievement, institutional dedication and sociological variables linked to examples of the survey questions shown in Figure 3-28 and coded in Appendix 6 (O).

The questions span a range of topics, from user-friendliness to the relevance of assignments. The questions draw upon the theories of Bean and Tinto and Eisner's views on qualitative inquiry. Using the statistics tool, factoring, the results of the questions are coded between the psychological, social, economic, organisational, and environmental constructs, as illustrated in Table 3-10.

Table 3-10 Survey Questions Related to Constructs

Statement	**Psychological**	**Social Dynamics**	**Economic**	**Organisational**	**Environmental**
The lecturer is well-prepared and on time.	✓	✓		✓	
Knowledgeable about the subject	✓	✓	✓	✓	✓
Adequacy of teaching facilities		✓	✓	✓	✓
Explanation of assessment weightings	✓	✓	✓	✓	✓
Prompt return of marked tasks	✓	✓	✓	✓	✓
Clear instructions for assignments	✓	✓	✓	✓	✓
Students' embedded knowledge	✓	✓			
Fairness of assessment	✓	✓	✓	✓	✓
Ease of use of Connect		✓	✓	✓	✓

The outline below explains the constructs of Table 3-10.

- Psychological – questions about student readiness, the relevance of assignments, and the directing function of SmartBook® align here as they touch upon student engagement, motivation, and cognitive strategies (Tajibayeva et al., 2023).
- Social – questions concerning the ease of use of Connect and recommendations to other universities fall under this construct. These inquiries address user interaction and the broader academic community's perception (Shinwari et al., 2023).
- Economic – the question on the value addition of Connect in Financial Management

may reflect an economic construct, as it concerns cost-benefit analysis and resource allocation (Yu et al., 2023).

- Organisational – questions regarding integrating Connect into the curriculum and whether it should be a part of the lecturer's toolkit are organisational. They deal with the structure and dissemination of the learning content (Alfirević et al., 2023).
- Environmental – the suggestion of moving exams and tests online implicates ecological considerations, such as the digital learning environment and infrastructural needs (Abdigapbarova & Zhiyenbayeva, 2023).

Eisner's (2017) assertion that qualitative inquiry transcends disciplinary boundaries supports the notion that these questions, while specific to a learning and teaching context, can yield insights with implications across various dimensions of the learning experience. Each question probes a different layer of the scholarly ecosystem, collectively informing an institution's approach to integrating technology into learning.

To link the survey questions to the frameworks by Bean and Tinto, as well as Eisner's perspective on qualitative inquiry, I considered the following aspects:

- Bean's Student Attrition Models: Bean's models focus on student retention, suggesting that learning experiences, including online tools, influence students' decisions to persist in their education (Bean, 1980).
- Tinto's Theory of Student Departure: According to Tinto's (1975) retention theory, institutional integration through social and academic intellectual manners determines retention. Concerning the question related to the ease of use and recommendation of Connect, respondents answered the question about social integration. On the other hand, it is significantly more relevant to identify how online exams and tests in Connect® influence academic integration.

Eisner's Perspective on Qualitative Inquiry: Eisner suggests that qualitative inquiry is holistic and transcends disciplines, focusing on the value and meaning of experiences. Survey questions examine the direct impact and potential of learning in the broader environment. It discusses the effects on learners regarding Psychology and how organisations embrace the new technologies in online learning (Eisner, 2017).

Descriptive research design has various specific purposes. The most common non-experimental research design involves identifying the factors and generalisable characteristics of sets, learning and teaching research, mainly where the intent is to identify similarities and differences. The most appropriate technique recognised is the Factorial analysis (Rouder et al., 2023). In Beavers's (2019) study, the author surveyed 45 manuscripts and provided a systematic review to examine and synthesise the literature to systematically evaluate factorial evaluation learning and teaching research contributions, particularly to assess the sample size and its relation to correlation joint factor analysis. Beavers's (2019) study determined that exploring the first structure requires a minimum sample size of 150. Accordingly, this study exceeded the suggested sample size as it had more than 5,000 survey results, as in Appendix 6 (P). Table 3-8 illustrates the coding applied to the survey questions to conduct the factoring, including Correlation Mix, Kaiser-Meyer-Olkin (KMO) and Bartlett's test, Commonalities, Total Variances, Component Mix and Rotated Mix shown in Table 3-7. The analysis used factorial analysis to gain a multidimensional understanding of the issues. This approach contextualised the archival data within broader academic discussions (Yu et al., 2023; Abdigapbarova & Zhiyenbayeva, 2023; Tajibayeva et al., 2023; Likert, 1932; Kriksciuniene et al., 2019). The grade and pass rate data are analysed using t-tests.

3.9.6.4 Grades and Pass Rates: Reflexive Analysis

The performance focuses on the course's efficacy in achieving educational goals, such as skill acquisition, material comprehension, and knowledge application in assessments. The assessment indicates which learning objectives the students are achieving at which level outlined by the course. This theme might consist of concepts and questions like:

- Clarity of Assessment Criteria: By doing this, explanations about the proper evaluation methods help learners direct their study efforts towards the right end.
- Fairness and Appropriateness of Testing: Some questions include whether instructors develop exams coupled with assignments to raise the competency levels of learners or whether they model them sufficiently to determine the competency levels of learners.
- Adequacy of Instruction: Feedback on whether the lecturer's instructions help students perform tasks and assignments effectively.
- Overall Course Effectiveness: Ratings that directly ask students to evaluate how well the course prepares them in their subject area or discipline see Figure 3-29.

3.9.6.5 Grades and Pass Rates: t-Test

The statistical methods illustrated in Table 3-3 summarise the analysis and tests used and their objectives. Figure 3-31 shows the combined Excel spreadsheet of the final grades and pass rates per course and year used for the statistical analysis tool, as Appendix 6 (X).

Conducting a T-test compares the means of two independent groups if they meet the independence criteria. When there are more than two groups, however, it is necessary to determine if there are any differences in their means. T-test analysis is a popular statistical method used for this purpose (Rouder et al., 2023). This study explored the importance of using ANOVA (analysis of variance) instead of a t-test. ANOVA provides a conceptual explanation of comparing the variances instead of the means themselves and explains the differences in standards between multiple groups (Rouder et al., 2023). ANOVA, however, must use the same variable, making this analysis irrelevant. Grades and Pass rates are two separate variables; hence, the t-test was appropriate.

Figure 3-29 Grade and pass rates used in the t-test analysis and Appendix 6 (X) provide additional source grade and pass rate data pre- and post-platform implementation data. As illustrated in Figure 3-30, the data is consolidated and cleaned for statistical analysis.

Summary of All Courses						
Raw Data from Institution data Base						
Course	**Enrolments**	**Passed**	**Pass Rate-Pre Intervention**	**Average Final Mark Pre Intervention**	**Year**	**Mode**
FINANCIAL MANAGEMENT 4 (FMA400S)	80	61	76.25%	57.51%	**2017**	Pre-Intervention
FINANCIAL MANAGEMENT 3 (FMA301S)	196	167	85.20%	59.46%	**2017**	Pre-Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	240	200	83.33%	58.38%	**2017**	Pre-Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	31	27	87.10%	58.23%	**2017**	Pre-Intervention
FINANCIAL ACCOUNTING 1 (FIA10SX)	35	27	77.14%	60.73%	**2017**	Pre-Intervention
FINANCIAL ACCOUNTING 1 (FIA102S)	206	139	67.48%	58.55%	**2017**	Pre-Intervention
FINANCIAL ACCOUNTING 1 (FIA102S)	48	35	72.92%	67.18%	**2017**	Pre-Intervention
FINANCIAL MANAGEMENT 4 (FMA400S)	54	45	83.33%	52.98%	**2018**	Pre-Intervention
FINANCIAL MANAGEMENT 3 (FMA301S)	236	202	85.59%	58.44%	**2018**	Pre-Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	177	130	73.45%	51.88%	**2018**	Pre-Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	41	31	75.61%	57.18%	**2018**	Pre-Intervention
FINANCIAL MANAGEMENT 1 (FMG150X)	29	24	82.76%	60.26%	**2018**	Pre-Intervention
FINANCIAL MANAGEMENT 1 (FMG150S)	161	122	75.78%	57.23%	**2018**	Pre-Intervention
FINANCIAL MANAGEMENT 4 (FMA400S)	52	41	78.85%	51.71%	**2019**	Pre-Intervention
FINANCIAL MANAGEMENT 3 (FMA301S)	202	165	81.68%	60.91%	**2019**	Pre-Intervention
FINANCIAL MANAGEMENT 2 (FMG260S)	121	99	81.82%	56.99%	**2019**	Pre-Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	76	42	55.26%	46.35%	**2019**	Pre-Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	30	22	73.33%	56.97%	**2019**	Pre-Intervention
FINANCIAL MANAGEMENT 1 (FMG150X)	26	17	65.38%	53.74%	**2019**	Pre-Intervention
FINANCIAL MANAGEMENT 1 (FMG150S)	157	102	64.97%	50.22%	**2019**	Pre-Intervention
FINANCIAL MANAGEMENT 1 (FMG150S)	28	16	57.14%	48.27%	**2019**	Pre-Intervention
Course	**Enrolments**	**Passed**	**Pass Rate-Post Intervention**	**Average Final Mark Post Intervention**	**Year**	**Mode**
INVESTMENT ANALYSIS (IVA470S)	20	19	95.00%	75.05%	**2020**	Intervention
FINANCIAL MANAGEMENT 4 (FNM470S)	70	59	84.29%	58.00%	**2020**	Intervention
FINANCIAL MANAGEMENT 4 (FMA400S)	11	10	90.91%	52.36%	**2020**	Intervention
FINANCIAL MANAGEMENT 3 (FMG360S)	94	85	90.43%	54.41%	**2020**	Intervention
FINANCIAL MANAGEMENT 3 (FMA301S)	92	85	92.39%	61.65%	**2020**	Intervention
FINANCIAL MANAGEMENT 2 (FMG260S)	137	98	71.53%	51.57%	**2020**	Intervention
FINANCIAL MANAGEMENT 2 (FMG260S)	16	15	93.75%	62.33%	**2020**	Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	26	19	73.08%	52.38%	**2020**	Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	13	9	69.23%	48.54%	**2020**	Intervention
FINANCIAL MANAGEMENT 1 (FMG150X)	6	2	33.33%	33.83%	**2020**	Intervention
FINANCIAL MANAGEMENT 1 (FMG150S)	183	134	73.22%	53.20%	**2020**	Intervention
FINANCIAL MANAGEMENT 1 (FMG150S)	24	18	75.00%	47.00%	**2020**	Intervention
INVESTMENT ANALYSIS (IVA470S)	30	26	86.67%	57.93%	**2021**	Intervention
FINANCIAL MANAGEMENT 4 (FNM470S)	59	51	86.44%	57.53%	**2021**	Intervention
FINANCIAL MANAGEMENT 4 (FMA400S)	1	0	0.00%	17.00%	**2021**	Intervention
FINANCIAL MANAGEMENT 3 (FMG360S)	119	116	97.48%	78.15%	**2021**	Intervention
FINANCIAL MANAGEMENT 3 (FMA301S)	35	34	97.14%	71.85%	**2021**	Intervention
FINANCIAL MANAGEMENT 2 (FMG260S)	176	128	72.73%	47.67%	**2021**	Intervention
FINANCIAL MANAGEMENT 2 (FMG260S)	19	16	84.21%	52.21%	**2021**	Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	9	5	55.56%	39.25%	**2021**	Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	4	3	75.00%	49.25%	**2021**	Intervention
FINANCIAL MANAGEMENT 1 (FMG150X)	17	11	64.71%	48.44%	**2021**	Intervention
FINANCIAL MANAGEMENT 1 (FMG150S)	204	130	63.73%	51.02%	**2021**	Intervention
FINANCIAL MANAGEMENT 1 (FMG150S)	21	17	80.95%	60.47%	**2021**	Intervention
INVESTMENT ANALYSIS (IVA470S)	40	39	97.50%	67.08%	**2022**	Intervention
FINANCIAL MANAGEMENT 4 (FNM470S)	76	63	82.89%	57.37%	**2022**	Intervention
FINANCIAL MANAGEMENT 4 (FMA400S)	1	1	100.00%	50.00%	**2022**	Intervention
FINANCIAL MANAGEMENT 3 (FMG360S)	138	136	98.55%	80.72%	**2022**	Intervention
FINANCIAL MANAGEMENT 3 (FMA301S)	12	10	83.33%	71.18%	**2022**	Intervention
FINANCIAL MANAGEMENT 2 (FMG260S)	171	123	71.93%	48.92%	**2022**	Intervention
FINANCIAL MANAGEMENT 2 (FMG260S)	18	15	83.33%	59.67%	**2022**	Intervention
FINANCIAL MANAGEMENT 2 (FMA201S)	2	2	100.00%	50.00%	**2022**	Intervention
FINANCIAL MANAGEMENT 1 (FMG150X)	52	35	67.31%	52.84%	**2022**	Intervention
FINANCIAL MANAGEMENT 1 (FMG150X)	29	25	86.21%	63.00%	**2022**	Intervention
FINANCIAL MANAGEMENT 1 (FMG150S)	197	133	67.51%	52.06%	**2022**	Intervention
FINANCIAL MANAGEMENT 1 (FMG150S)	15	5	33.33%	38.92%	**2022**	Intervention
	4363	**3391**	**77.72%**			
			76.51%	**54.78%**		

Figure 3-29 Grade and pass rates used in the t-test analysis

	Intervention		Pre-Intervention		Total Sum of Pass Rate	Total Sum of Average Final Mark
Row Labels	Sum of Pass Rate	Sum of Average Final Mark	Sum of Pass Rate	Sum of Average Final Mark		
⊟ FINANCIAL MANAGEMENT 1						
2017			69.55%	62.15%	69.55%	62.15%
2018			76.84%	58.75%	76.84%	58.75%
2019			63.98%	50.74%	63.98%	50.74%
2020	72.30%	50.10%			72.30%	50.10%
2021	65.29%	53.31%			65.29%	53.31%
2022	67.58%	51.71%			67.58%	51.71%
⊟ FINANCIAL MANAGEMENT 2						
2017			83.76%	58.31%	83.76%	58.31%
2018			73.85%	54.53%	73.85%	54.53%
2019			71.81%	53.44%	71.81%	53.44%
2020	73.44%	53.71%			73.44%	53.71%
2021	73.08%	47.10%			73.08%	47.10%
2022	73.30%	52.86%			73.30%	52.86%
⊟ FINANCIAL MANAGEMENT 3						
2017			85.20%	59.46%	85.20%	59.46%
2018			85.59%	58.44%	85.59%	58.44%
2019			81.68%	60.91%	81.68%	60.91%
2020	91.40%	58.03%			91.40%	58.03%
2021	97.40%	75.00%			97.40%	75.00%
2022	97.33%	75.95%			97.33%	75.95%
⊟ FINANCIAL MANAGEMENT 4						
2017			76.25%	57.51%	76.25%	57.51%
2018			83.33%	52.98%	83.33%	52.98%
2019			78.85%	51.71%	78.85%	51.71%
2020	85.19%	55.18%			85.19%	55.18%
2021	85.00%	56.33%			85.00%	56.33%
2022	83.12%	58.52%			83.12%	58.52%
⊟ INVESTMENT ANALYSIS						
2020	95.00%	75.05%			95.00%	75.05%
2021	86.67%	57.93%			86.67%	57.93%
2022	97.50%	67.08%			97.50%	67.08%
Grand Total	**12.43581885**	**8.87848333**	**9.307064944**	**6.78923333**	**21.74288379**	**15.66771667**

Figure 3-30 Consolidated sum of grade and pass rates used in the t-test analysis

Source of data is required to apply the statistical tools and serve as part of the methodological integration.

3.10 Methodological Integration

This study used a triangulated converged mixed approach case study to address the research questions. It included understanding opinions and a number-based analysis, testing ideas. It looked at how AI tools influence student views on engagement with a platform, performance, and retaining students in the system.

3.10.1 Integrative Mixed-Methods Approach

A mixed-methods approach was logical, providing a more comprehensive understanding than any single method. This strategy combined the broad applicability of quantitative data with the detailed insights of qualitative data.

3.10.2 Methodological Triangulation Integration

Triangulation, through diverse research methods, enhanced the credibility of the findings. It ensured the results accurately represented the observed reality, not merely artefacts of a specific process.

3.10.3 Qualitative Data: Thematic Integration

The thematic integration made the analysis accessible to the process by combining the students' experiences with the thematic and statistical approaches. In learning and teaching research concepts and methods, assessing and defining the effects of intercessions on student performance, engagement, and satisfaction level is imperative. Some things must be considered to make a better and more well-reasoned decision, especially between two reasonable parties, like a university and its students. All in all, the approach worked because it used qualitative and quantitative findings in synchronicity. This issue demonstrated how students would benefit from AI peer interaction and even increase their performance through interaction with AI.

3.10.4 Quantitative Data: Statistical Analysis Integration

Establishing pass rates and average final marks was done to determine the impact of the AI platform on altering grade performance. It assessed the overall performance of the student's grades by conducting statistical measurements on the obtained raw data and evaluated the students' overall performance. Another significant feature of the study was that it used archival surveys to ensure the validity and reliability of the findings. It outlined valuable strategies for meeting the research questions and objectives.

3.11 Data Overview and Limitations

Data was accessed and analysed from the institutional database covering 2017-2023 and was limited to final published student grade data and student surveys conducted during this period with certain limitations, as shown in an example Appendix 6 (GG).

3.11.1 Limited Scope

The research focuses on the relationship between hours spent in the course and marks obtained and the relationship between perception and the likelihood of engaging with the platform. It did not explore other factors influencing these relationships, such as individual differences, study habits, or external variables.

3.11.2 Generalisability

The investigation provides insights based on the specific sample or population studied. The findings and conclusions may only be universally applicable to contexts, people, or learning settings, and there is a possibility of limited generalisability of the results.

3.11.3 Causality

The study provides notable evidence that directs one towards the fact that there may exist correlations of the variables regardless, which prompts the idea that causation is also present. The study acknowledges the possibility of other factors affecting the outcome observations, underscoring the desirability of future attempts to identify cause-and-effect relations.

3.11.4 Subjectivity and Bias

The study's limitations regarding methodology include the fact that the research does not consider any biases or other modes of subjectivity in the data collection and analysis process. It is fundamental to realise that the results depend on the perspectives or prejudices of the researchers or on the errors, chance findings, or preferential analysis that the latter can accidentally introduce.

Table 3-11 Potential Biases and Mitigation Strategy

Type of Bias	Description	Impact	Mitigation Strategy
Confirmation Bias	Emphasising data that confirms beliefs about AI's positive impact.	Overlooking negative or neutral outcomes of AI integration.	Regular self-reflection; triangulating data sources.
Cultural and Contextual Bias	Assuming AI interventions are universally applicable.	Overgeneralisation without considering diverse socio-cultural contexts.	Ensuring cultural and contextual sensitivity; peer review for diverse perspectives.
Technology Optimism Bias	I view AI as a transformative tool, possibly overestimating benefits.	Inadequate focus on AI's limitations, like accessibility issues or resistance.	Documenting both successes and challenges; transparent reporting.
Selection Bias	Choosing participants is likely to show positive outcomes.	Results may not be generalisable to the broader student population.	Use randomised sampling to ensure participant diversity.
Interpretive Bias	I am interpreting qualitative data to align with expectations.	I am emphasising supportive narratives while downplaying criticisms.	Involving multiple reviewers for data interpretation; reflexivity in analysis.
Intervention Bias	I am designing AI interventions based on my teaching philosophy.	Interventions may not be effective for all students or contexts.	Developing interventions based on diverse input; pilot testing interventions.
Data Interpretation Bias	I am attributing positive outcomes primarily to AI support.	Overlooking other factors contributing to changes in performance.	Cross-analysing with other factors, including a control group.
Ethnocentric Bias	I am interpreting findings mainly through the South African context.	Limited applicability of findings to other educational settings.	Comparative analysis with other contexts; international peer review.
Role Conflict Bias	Influence of lecturer role on conservative reporting.	Underreporting challenges to preserve professional reputation.	Clear separation of roles in reporting; external validation.
Outcome Bias	Favouring interpretations that lead to positive conclusions.	I am overemphasising positive aspects while downplaying neutral/negative outcomes.	Transparent documentation; seeking external review to balance interpretations.

Table 3-11 concisely captures the potential biases, their impact, and strategies to mitigate them in the thesis research.

3.11.5 Contextual Factors

The study lacks contextual factors to test the effects of various correlations under analysis. It will also be pivotal to note that those variables, like the difficulty level of the course or the calibre of the teacher, are not eliminated from consideration. Still, they are not included in the study even though most give direction to the outcome.

3.11.6 Limited Variables

The study highlights several variables systematically while omitting the contingency of other variables that could affect the relationship explored.

The limitation of the study is that the research is specific to one country and does not try to make broader conclusions, and there are no causation claims. It also recognises limitations and speculations that may conceal probabilities affecting the results. Thus, future claims or policy suggestions should consider these limitations to avoid misunderstanding the scope of the reproduced findings and to direct research efforts to generate even more valid data in the future.

3.12 Ethical Considerations

This research prioritises ethical considerations, including privacy protection, non-discrimination, and data used solely for educational purposes (Verbeke et al., 2023). The study uses the university's pre-existing academic and survey records, thus dropping the need for individual consent. Further, the research method ensures participant anonymity and minimises potential harm (Lundgren, 2023). The researcher had requested and obtained university approval to access and use the data, reaffirming the research's exclusive purpose. The researcher obtained approval from the university's Ethics Committee, see Appendix 1 Site Approval and site permission to use the data. McGraw Hill™ approved utilising the platform for study purposes. See the details in Appendix 6 (DD). While individual consent is still an ethical research cornerstone, it is waived here due to the low-risk nature of analysing existing anonymised data (Lundgren, 2023).

Transparency is maintained by articulating the study's rationale and processes to the institution, clarifying it as a private doctoral study conducted by the Cape Peninsula University of Technology, and informing students about the purpose of the bi-annual survey via the LMS system. The study guaranteed anonymity to students who participated voluntarily.

3.13 Conclusion

The study uniquely focused on exploring the influence of an artificial intelligence platform in helping peer-to-peer learning, referencing engagement and academic achievement, which is distinct from general IT-related teaching systems. While other studies regarding technology and learning and teaching may exist, the scope here zeroes in on peer-to-peer frameworks facilitated by AI. Therefore, it advances beyond the over-researched arena of general IT efficacy in learning and teaching. AI's pervasive influence on multiple contexts impacts peer-to-peer learning.

The study meticulously analyses archival data for recurring themes that resonate with the vital elements of peer-to-peer learning, focusing on how AI enhances individualised learning experiences. This analysis builds on the premise that the impacts of AI in personalising learning—such as customising content and pacing according to individual needs—can be effectively translated into peer-to-peer learning contexts and retention. Nineteen archival surveys reveal that AI's role in personalising learning experiences can benefit individuals and enhance peer interactions. By aligning students with similar learning goals or challenges, AI can facilitate meaningful exchanges, extending the benefits of personalised learning into the collective learning environment. Its adaptive mediate ability also links individual enhancement to better peer-to-peer learning outcomes.

The study acknowledges the complexities surrounding the link between performance and retention rates, using a cross-sectional analysis from 2017 to 2023 to provide a more credible understanding of engagement, performance and peer-to-peer support. The study aimed to provide a comprehensive exploration using multidimensional metrics and a pragmatic assumptive paradigm rather than establishing causality. Therefore, the focus is not merely on whether AI platforms are effective but on how they intersect with peer-to-peer learning paradigms to potentially influence performance, engagement and retention.

CHAPTER 4 RESULTS

This chapter presents detailed findings on the thematic effects of an AI-peer platform on student engagement. It examines whether students believe the system can improve their grades and if it effectively serves as a peer-to-peer academic support service. As part of the study rigour, student grades and pass rates are statistically analysed pre- and post-AI intervention to ascertain if the AI peer platform affected grades and pass rates.

Based on student perception, thematic examination centres on three primary analyses offered by the AI platform for learner progression, namely:

- Features of the platform include a peer-to-peer support pillar.
- Improvement in engagement occurs with the course, leading to increased performance levels.
- Expected performance levels manifest in grade outcomes while using the platform.

The alleged degree of student engagement is integral to this research, which evaluates students' views on the platform and their perceived performance. The thematic analysis is helpful as it suggests that these perceptions may create practical learning and teaching practices of AI-peer platforms. The study provides a descriptive statistical data analysis to avoid potential measurement errors. The analysis grounds this methodology for tracing the platform's impact on student's grades and pass rates by comparing their results before and after the intervention and its ability to leverage its features as a peer.

This chapter explores the reciprocal relationship between student engagement and their perception of performance while highlighting the importance of engagement in raising academic self-efficacy, thereby addressing the research questions. It focuses on the relationships between the AI peer-to-peer support platform, student engagement and grade achievement. This chapter empirically examines the correlation between student engagement and their perceived performance, focusing on how engagement leads to increased self-efficacy. Potentially, the feasibility of the AI platform allows students to communicate, work in groups, and get feedback from the course content, leading to increased motivation and impacting their academic performance.

These results, depicted in various figures and tables throughout the chapter, could demonstrate the ongoing and interconnected nature of the study's outcomes.

The thematic analysis seeks to demonstrate that students are active learners and, therefore, the importance of individualised AI peer-to-peer communication in producing quality results. Subsequent statistical analyses by theme, peer-to-peer, engagement, grades and pass rates will validate these findings and extend our understanding of the effects of engagement and performance on learning.

The study focuses on AI-facilitated peer-to-peer support platforms, emphasising student interactions, collaborative learning, and group activities. The core themes revolve around engagement, examining how the platform influences student involvement and interest in the course. Additionally, the study addresses achievement and analyses the impact of the AI platform on grades, pass rates, and overall student performance.

4.1 Introduction

I collected data from five courses between 2019 and 2022, collating 4467 raw natural data entries and entering them into Excel for analysis (Eisner, 2017). The information is part of the study data to determine the AI peer-to-peer support factors influencing engagement, grades and pass rates. The study had a good sample size, with an average class size of 240 and a response rate of 39%. The survey contained 157 questions, and the responses reached 13,829, making the data diverse. The study groups the questions into theoretical frameworks, including intellectual development, peer group interactions, and faculty interactions. The raw data is in the eSonga repository. Figshare. https://figshare.com/s/1f6173c54222ce2d4705 (Wilson-Trollip, 2024) and offers additional references. This grouping leads us to a detailed statistical factoring examination of engagement. Acknowledging that this dataset pertains solely to one university and may not comprehensively represent the learner population across different institutions is instrumental. The sample was sufficiently large (N = 2668 population size, 1028 respondents, 39%), as shown in Table 4-1.

Table 4-1 Sample Population

Year	Population	Respondents	%Response
2019	279	118	42%
2020	879	198	23%
2021	918	405	44%
2022	616	132	21%
Total	2668	1028	39%
Average	**534**	**206**	**39%**

The dataset totalled 157 questions across nineteen surveys. Appendix 6 (P) provides additional data on the total responses to the questions, totalling 13829. Two thousand six hundred sixty-eight learners received the questionnaires, and 1028 replied, yielding a 39% response rate. Wu, Zhao and Fils-Aime (2022) found that the average response rate from online studies is 44.1%. The study evaluates the platforms' effectiveness in engagement and belief by assessing the validity of each question per thematic category (Bohrnstedt & Marwell, 1978; Bacharach, 1989). The population scope exceeded the recommended threshold of a minimum of 100 to 200 respondents as per McNeish & Wolf (2023) and is considered substantial with 206.

Table 4-2 presents the total number of questions replied to according to the five categories.

Table 4-2 Replies per Categories Framework

Framework	Number of Replies
Tinto Framework-Psychological Belief Motivation	1126
Tinto Framework-Organisation Structure Efficiency	67
Bean Framework-Organisation Structure Efficiency	192

Framework	Number of Replies
Bean Framework-Social Dynamics Cooperation Inclusion	1088
Bean Framework-Psychological Belief Motivation	7749
Total	**10228**

The analysis excludes some questions, as the number of responses (13,829) aligns differently with the categorised replies (10,228) due to incompatible categories. Specific questions with missing values (26%) remain uncategorised under any type, thus not contributing to category score calculations.

Table 4-3 Missing Values

Number of Answered Questions	Categorised Replies	Missing values
13829	10228	4 %)

Table 4-3 classifies these as missing values for the context of category analysis. The data results begin with the combined qualitative findings of the impact of AI peer-to-peer support on engagement, grade, and pass rates from the performance thematic analysis. The chapter presents further findings from the quantitative statistical analysis of grade and pass rate achievement. Figure 4-1 in the next section illustrates students' combined average responses based on their perceptions and beliefs regarding AI peer-to-peer support influencing engagement, peer-to-peer support, grades and pass rates.

4.2 Student's Belief in AI Influencing Peer Support, Engagement, Grades and Pass Rates

The average responses summarised in Table 4-4 and Table 4-5 from the raw data are per students’ perceived beliefs about AI peer-to-peer support and how it influences engagement, peer support, grades, and pass rates.

Table 4-4 Average Summary Analysis of Engagement, Peer-to-Peer Support, Grades and Pass Rates

Engagement										
	Strongly Agree	Agree	Neutral	Disagree		Strongly Agree	Agree	Neutral	Disagree	
Essential	10,68%	1,80%	0,27%	0,00%	**12,76%**	83,74%	14,12%	2,14%	0,00%	**100,00%**
Important	7,79%	0,94%	0,05%	0,11%	**8,88%**	87,64%	10,54%	0,58%	1,24%	**100,00%**
Considerable	8,15%	1,08%	0,21%	0,13%	**9,57%**	85,15%	11,27%	2,21%	1,37%	**100,00%**
Minor	2,04%	0,42%	0,04%	0,01%	**2,51%**	81,26%	16,78%	1,45%	0,50%	**100,00%**
Total	**28,65%**	**4,24%**	**0,57%**	**0,25%**	**33,71%**	84,98%	12,57%	1,70%	0,75%	**100,00%**
Peer-to-Peer Support										
	Strongly Agree	Agree	Neutral	Disagree		Strongly Agree	Agree	Neutral	Disagree	
Essential	5,67%	0,63%	0,08%	0,00%	**6,38%**	88,86%	9,84%	1,30%	0,00%	**100,00%**
Important	16,19%	1,73%	0,12%	0,41%	**18,45%**	87,76%	9,38%	0,64%	2,22%	**100,00%**
Considerable	2,37%	0,29%	0,08%	0,00%	**2,73%**	86,68%	10,55%	2,77%	0,00%	**100,00%**
Minor	0,99%	0,10%	0,05%	0,00%	**1,14%**	86,74%	8,54%	4,72%	0,00%	**100,00%**
Total	**25,22%**	**2,74%**	**0,33%**	**0,41%**	**28,70%**	87,86%	9,56%	1,15%	1,43%	**100,00%**
AI and Grades										
	Strongly Agree	Agree	Neutral	Disagree		Strongly Agree	Agree	Neutral	Disagree	
Essential	20,58%	1,93%	0,02%	0,26%	**22,78%**	90,33%	8,48%	0,07%	1,12%	**100,00%**
Important	7,46%	0,67%	0,07%	0,00%	**8,20%**	90,96%	8,13%	0,91%	0,00%	**100,00%**
Considerable	5,15%	0,57%	0,04%	0,16%	**5,92%**	86,95%	9,63%	0,70%	2,72%	**100,00%**
Minor	0,32%	0,26%	0,03%	0,07%	**0,68%**	47,40%	38,47%	4,53%	9,60%	**100,00%**
Total	**33,51%**	**3,43%**	**0,16%**	**0,48%**	**37,59%**	89,15%	9,13%	0,43%	1,28%	**100,00%**
Total	**87,38%**	**10,41%**	**1,06%**	**1,15%**	**100,00%**	87,38%	10,41%	1,06%	1,15%	**100,00%**
				100,00%						

Table 4-5 Average Combined Summary Analysis of Engagement, Peer-to-Peer Support, Grades and Pass Rates

	Strongly Agree	Agree	Neutral	Disagree	Total
Essential	87,64%	10,81%	1,17%	0,37%	100,00%
Important	88,79%	9,35%	0,71%	1,15%	100,00%
Considerable	86,26%	10,48%	1,89%	1,36%	100,00%
Minor	71,80%	21,26%	3,57%	3,37%	100,00%
Total	**83,62%**	**12,98%**	**1,83%**	**1,56%**	**100,00%**

Figure 4-1, compiled from Table 4-5, shows the students' perceptions regarding the impact of AI on three main combined areas: peer-to-peer support, engagement, and achievement. Peer-to-peer categorised questions focused on student interactions, collaborative learning, and group activities. Questions categorised as engagement involve student participation and interest in the course. Questions relating to achievement relate to assessments, outcomes, and how effectively the course and its components support student achievement.

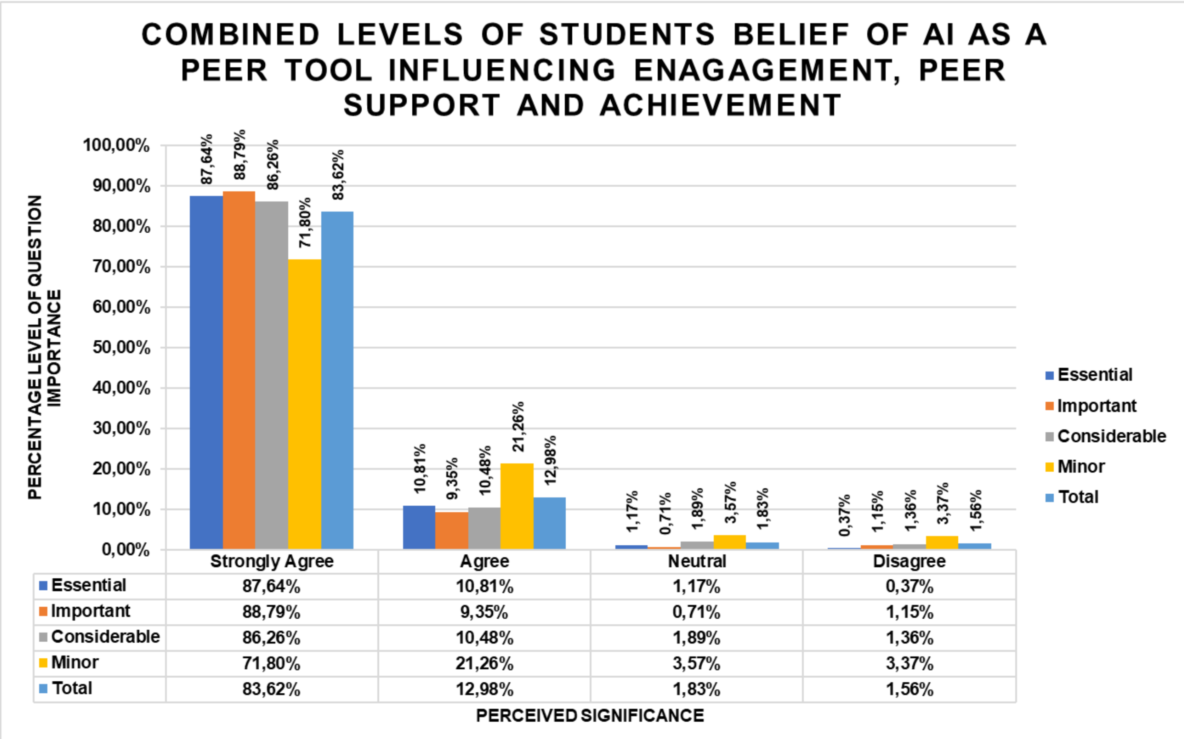

Figure 4-1 Combined Perception of AI Peer-to-Peer Support

The study categorises students' responses into four levels: strongly agree, agree, neutral, and disagree. Each category reflects the significance of the survey questions based on the works of Tinto (1975), Bean (1980) & Bork's (2002) framework: Essential, Important, Considerable, and Minor. For additional natural raw data, refer to Appendix 6 (GG). These allocations ensure that the factors directly affecting student learning and course success receive the most emphasis:

- Essential aspects are essential for the course's success and directly impact student learning outcomes. Given the highest priority, as these aspects are vital for the course's success and directly impact learning outcomes, one might allocate 40-50% of the points.
- Important factors significantly affect the quality of the educational experience but may not be as pivotal as essential factors. A reasonable allocation could be 25-30% of the points.
- Considerable elements influence student satisfaction or course functionality but are

less central to the core educational objectives. Hence, I allocated 15-20% of the questions to those deemed considerable.

- Minor, peripheral aspects have minimal impact on the overall educational effectiveness but might affect specific students or situations. These have minimal impact on overall educational effectiveness, so that they could receive 5-10% of the points.

4.2.1 Thematic Interpretation

This bar chart shows the viable percentage of all students who felt that AI as a peer tool impacts engagement, support, and achievement. Subsequently, based on the perceived significance of AI and the importance of the questions identified in this study, Figure 4-1 depicts the distribution of response values at different levels.

High Significance: Over half of the respondents (83. 62% strongly agree/ 12. 98% agree) state that AI peer-to-peer support plays a role in engagement, peer support, and achievement.

Low Significance, 1.83% and 1.56%, a low result shows AI peer-to-peer support has almost no importance and impact on student engagement, peer-to-peer, and achievement.

Overall Perception shows that the sum totals portray a preferred attitude of the respondents who strongly agree on the importance of AI as a peer tool.

4.3 Peer-to-Peer Support

It is reasonable to look at the students' use of increased AI peer-to-peer support with the identification of their academic success patterns in particular and in general. The connection between the two areas is that if the students' perceptions of their capability and the worth of the work are congruent, these perceptions enhance their participation in peer-to-peer support programs, including AI applications. They influence students' attitudes towards persistence and the implementation of the peer-support system, as well as their results. Illustrated in Figure 4-2 are the thematic findings of AI as a peer-to-peer support mechanism.

4.3.1 Thematic Interpretation

Table 4-6 and Figure 4-2 show the percentage of students' views on the effectiveness of an AI peer-to-peer support system and its influence on engagement. The data categorises responses into four levels of agreement: Strongly Agree, Agree, Neutral, and Disagree, with subcategories of Essential, Important, Considerable, and Minor.

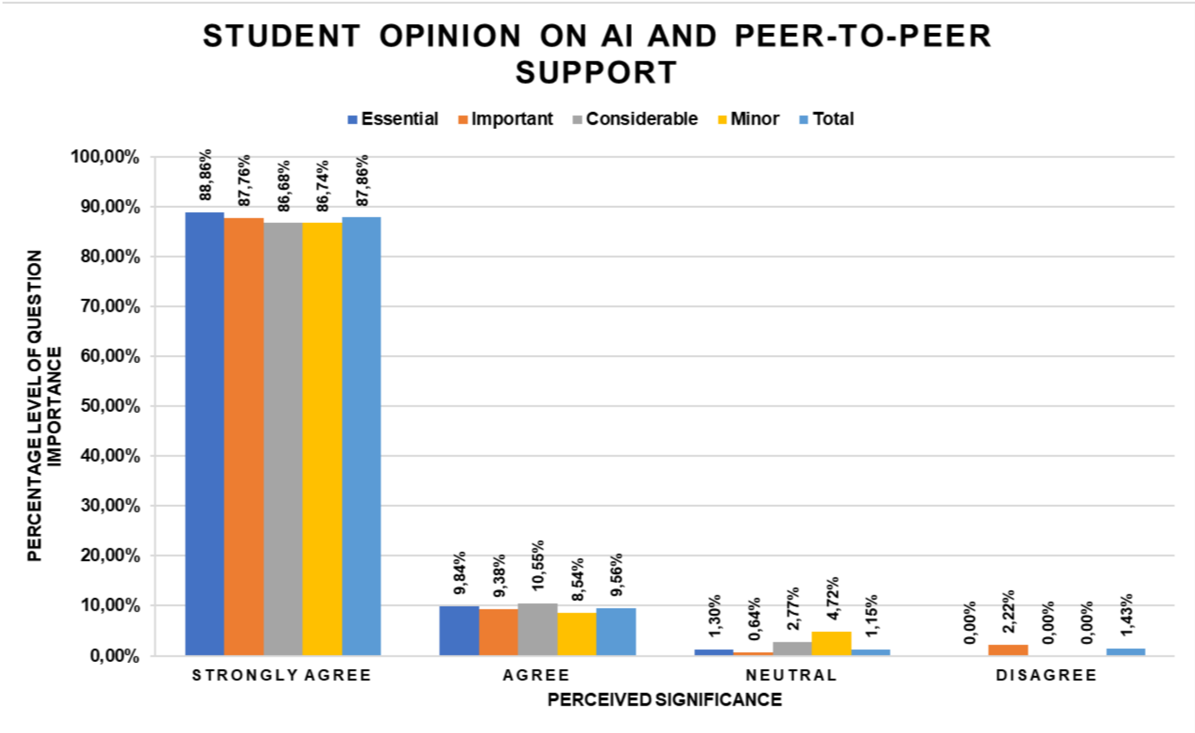

Figure 4-2 Student Opinion on AI and Peer-to-Peer Support

Table 4-6 AI and Peer-to-Peer Support

	Strongly Agree	% of Total	Agree	% of Total	Neutral	% of Total	Disagree	% of Total	Total	Sum % of Total
Essential	5.67%	88.86%%	0.63%	9.84%	0.08%	1.30%	0.00%	0.00%	6.38%	100.00%
Important	16.19%	87.76%	1.73%	9.38%	0.12%	0.64%	0.41%	2.22%	18.45%	100.00%
Considerable	2.37%	86.68%	0.29%	10.55%	0.08%	2.77%	0.00%	0.00%	2.73%	100.00%
Minor	0.99%	86.74%	0.10%	8.54%	0.05%	4.42%	0.00%	0.00%	1.14%	100.00%
Total	**25.22%**	**87.86%**	**2.74%**	**9.56%**	**0.33%**	**1.15%**	**0.41%**	**1.43%**	**28.70%**	**100.00%**

More than 88% of the students strongly agreed on the usefulness of the AI-peer platform in all the categories. Specifically, 88.86% consider it Essential based on the questions, 87.76% Important, 86.68% Considerable, and 86.74% Minor. This response shows that there is a firm agreement on the importance of the platform.

In the Agree category, the percentages are lower but still relatively high, with 9.84% finding it Essential, 9.38% Important, 10.55% Considerable, and 8.54% Minor. This result means that although a smaller group may not consider it crucial, they still appreciate it.

The Neutral responses are scarce, with only 1.15% in total, which means that most students have a clear stance on the platform. The breakdown shows 1.30% for Essential, 0.64% for Important, 2.77% for Considerable, and 4. 72% for Minor.

The Disagree category has the lowest percentage, thus showing a shallow level of disagreement. None of the students thought negatively about the platform not being Essential or Considerable. 2.22% considered it meaningful, and 1.43% disagreed in total.

In conclusion, the survey results indicate that students have a generally positive perception of the AI-peer platform and appreciate it as a valuable peer-to-peer support tool for learning. The low level of neutral and disagreement responses also supports the idea that the platform is helpful among students. I expect its influence on engagement to show similar results regarding its effect on engagement.

4.4 Engagement

Chapter Two established from the literature that It is fundamental to understand how AI can affect students' engagement, attitude, motivation, and long-term knowledge. Customising the learning experience is one way of keeping students engaged and has shown to be more efficient and effective than the conventional ways of teaching.

4.4.1 Thematic Interpretation

A possible way to customise the learning experience is through an AI peer-to-peer support platform, keeping students engaged and encouraging participation.

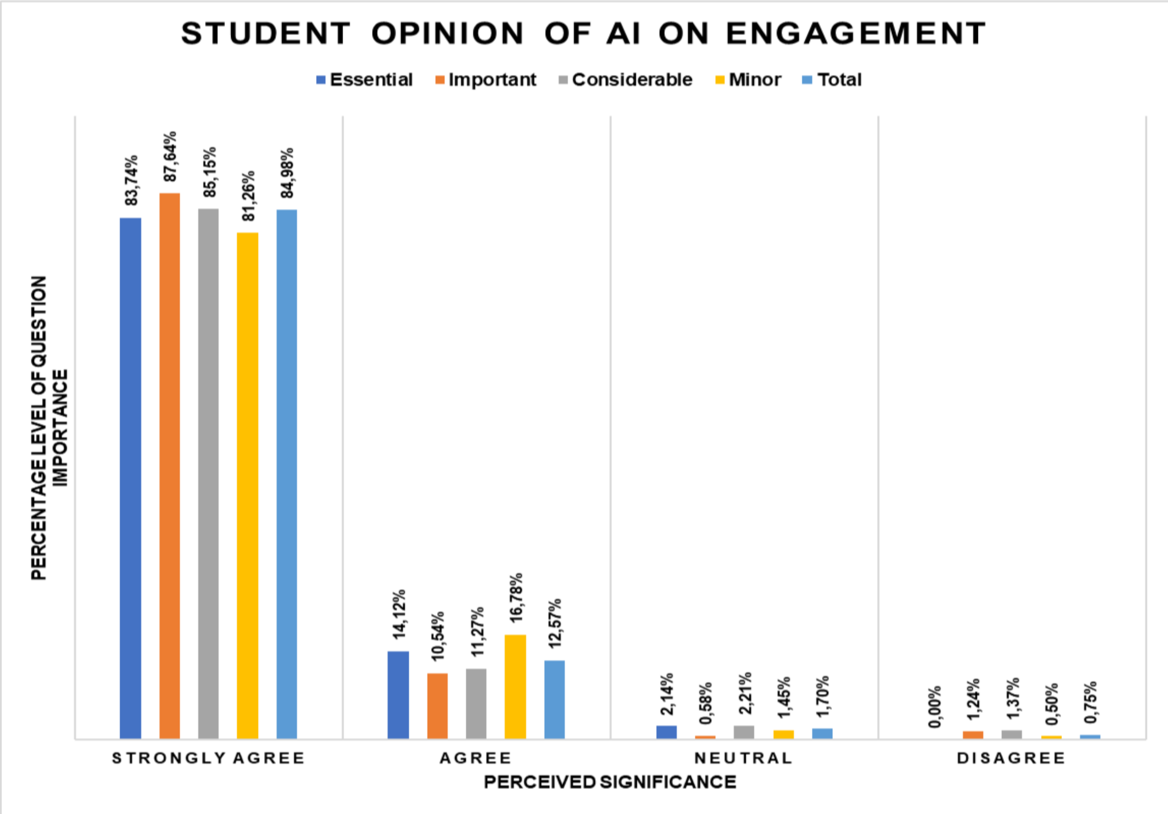

Figure 4-3 Student Opinion of AI on Engagement

Before understanding the data provided in Figure 4-3 Student Opinion of AI on Engagement, it is necessary to explain the distribution of the categories and the responses. These explanations are needed to understand the distribution of the responses shown in Table 4-7 Breakdown, by Category Engagement by the importance and perceived significance levels in the respective categories.

Table 4-7 Breakdown by Category Engagement

	Strongly Agree	% of Total	Agree	% of Total	Neutral	% of Total	Disagree	% of Total	Total	Sum % of Total
Essential	10.68%	83.74%	1.80%	14.12%	0.27%	2.14%	0.00%	0.00%	12.76%	100.00%
Important	7.79%	87.64%	0.94%	10.54%	0.05%	0.58%	0.11%	1.24%	8.88%	100.00%
Considerable	8.15%	85.15%	1.08%	11.27%	0.21%	2.21%	0.13%	1.37%	9.57%	100.00%
Minor	2.04%	81.26%	0.42%	16.78%	0.04%	1.45%	0.01%	0.50%	2.51%	100.00%
Total	**28.65%**	**84.98%**	**4.24%**	**12.57%**	**0.57%**	**1.70%**	**0.25%**	**0.75%**	**33.71%**	**100.00%**

To determine to what extent student engagement with the course changes by implementing AI peer-to-peer support depends on factors like the level of students' involvement in academic activities and their commitment to the university values and rules, academic self-efficacy, which refers to the level of confidence that students have in their academic achievement, and academic motivation which refers to the level of motivation of students to improve their performance.

Table 4-7 illustrates the thematic findings of the student's perceptions of their engagement with AI-facilitated peer-to-peer support and its effect on their engagement with the platform. The responses are categorised into four levels of agreement: Strongly Agree, Agree, Neutral, and Disagree, further breaking into Essential, Important, Considerable, and Minor. This explanation breaks down the data into more understandable segments, highlighting the relationship between question importance and student perception of significance.

A significant majority of total students, 84.98%, strongly agree on the essentialness of the AI platform in enhancing engagement. Specifically, 83.74% consider it Essential, 87.64% Important, 85.15% Considerable, and 81.26% Minor. This result indicates a strong consensus on the positive influence of the AI platform on student engagement.

The Agree category's percentages are lower but still reflect substantial support. 14.12% of students consider the platform Essential, 10.54% Important, 11.27% Considerable, and 16.78% Minor. 12.57% of all students agree. This finding suggests that while these students do not view the platform as fundamentally important, they still recognise its value in enhancing engagement.

The Neutral responses are minimal, with only 1.70% in total, indicating that most students have a definitive opinion on the platform's impact on engagement. The breakdown shows 2.14% for Essential, 0.58% for Important, 2.21% for Considerable, and 1.45% for Minor.

The Disagree category has the lowest percentages, indicating minimal opposition to the platform. No students disagreed with the platform being Essential, while 1.24% viewed it as Important, 1.37% as Considerable, and 0.50% as Minor.

Overall, the data reveals a strong positive reception towards the AI platform's impact on student engagement, with most students recognising its pivotal role. The minimal neutral and disagreement responses reinforce the platform's perceived value in enhancing student engagement. These values and descriptive statistical analysis provide insights into students' varying degrees of engagement perception, emphasising that most students view the platform as crucial to engagement.

4.4.2 Correlation Matrix

In Table 4-8, the correlation matrix reveals a determinant value of 0.078, providing valuable insights into the relationships between the variables.

Table 4-8 Correlation Matrix

Correlation
Matrix[a]
a. Determinant = .078

This variable correlation value offers several implications. It is important to note that correlated variables are desirable instead of complete independence. In this study, it is conceivable that the ease of using the AI platform might be related to the helpfulness of its content. However, the correlation coefficient matrix shows that these variables can hardly be independent, suggesting that there may be a link between them. It implies that student’s interactions with the platform would facilitate their engagement and the relevance of the content on the platform. This helpfulness means changing one aspect and suggesting ideas on how AI enhances learning.

The correlation matrix revealed the determinant value of 0.078. This value indicates that variables in my study related to AI's role in peer-to-peer learning are not entirely independent. There may be a relationship between the ease of using the AI platform and the helpfulness of its content. This finding suggests that improvements in one aspect might be linked to improvements in another, providing valuable insights into AI's facilitation of learning.

4.4.3 KMO and Bartlett's Test

Exploratory factor analysis yields the Kaiser-Meyer-Olkin (KMO) Measure and Bartlett's Test of Sphericity, which are crucial for analysis for both AI and peer-to-peer, as shown in Table 4-9.

Table 4-9 KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.789
Bartlett's Test of Sphericity	Approx. Chi-Square	270.307
	df	6
	Sig.	<.001

Kaiser-Meyer-Olkin (KMO) Measure: The KMO value ranges from 0 to one. This KMO value of 0.789 implies that the variables in my research are close enough to warrant steps for running the factor analysis. This measure means the data collected suits this kind of statistical analysis.

Bartlett's Test of Sphericity**:** Table 4-9 validates that the variables in my study are correlated. In simpler terms, it evaluates whether the variables are randomly related or have a meaningful pattern. The test yields a Chi-Square value, degrees of freedom (df), and significance level (Sig.). In this case, the Chi-Square value is 270.307 with 6 degrees of freedom, and the significance level is less than .001. This Chi-square is a strong indication that my variables are significantly correlated. It means that the variables in the study are not just randomly associated; there is a natural, meaningful pattern in how they are related.

These tests have the following implications:

- Data Suitability: The KMO value confirms that my data is suitable for factor analysis. This KMO value means I can confidently proceed that my analysis will be meaningful and dependable.
- The Pattern of Relationships: Bartlett's Test result supports the idea that there is a meaningful pattern in how the variables are related. This test is vital for understanding how different aspects of AI and peer-to-peer learning interact.
- Validation for Further Analysis: These tests validate my choice of factor analysis. They suggest that my analysis will provide insightful and valid results about how various factors influence peer-to-peer learning through AI.

The KMO value of .789 indicates that my data is suitable for factor analysis. Bartlett's Test suggests that the variables are significantly correlated, meaning their relation has a meaningful pattern. These tests validate my choice to use factor analysis in my study.

In summary, these test results indicate that my data is appropriate for factor analysis and that there are significant relationships among the variables, which is crucial for understanding the complex dynamics of AI in learning and teaching settings.

4.4.4 Commonalities

In this context of the study, commonalities are significant. Table 4-10 The commonalities show the variance percentage in each variable accounted for by the extracted factors in my factor analysis. This percentage indicates how well the factors represent each variable.

Table 4-10 Commonalities

Commonalities		
	Initial	**Extraction**
Are online classes easily accessible via Blackboard?	1.000	.835
Have you attended online classes in the last four weeks?	1.000	.833
If you have not attended online classes, why not?	1.000	.708
Should there be greater use of online learning	1.000	.613

Extraction Method: Principal Component Analysis.

4.4.4.1 Initial and Extraction Values

Table 4-10 addresses two types of commonality, namely:

- Initial commonalities are set initially at 1.000, assuming all variance in each variable is explainable before the factor analysis.
- Extraction commonalities-(.835, .833, .708 and .613) indicate how much of each variable's variance is explained by the extracted factors after the analysis. For example, a value of .835 for "Are online classes easily accessible via Blackboard?" demonstrates that 83.5% of the variance in this variable is due to the factors in the study.

In summary, the commonalities in my study indicate that the factors identified through factor analysis effectively capture a significant portion of the variability in student responses about online learning, which is vital for understanding and enhancing AI's role in learning and teaching.

4.4.4.2 Implications

Emergent implications include:

- Representation of variables: High extraction communalities (close to 1) indicate that the factors extracted in my analysis represent the variables well. Values like .835 and .833 suggest that the factors I have identified explain a large portion of the variance in how accessible online classes are and attendance in the last four weeks.
- Relevance of factors: The commonalities support the significance of the factors identified with AI's role in facilitating peer-to-peer learning. They suggest that these factors are significant in explaining students' experiences and behaviours in online learning environments.
- Strength of the model: High commonalities indicate a robust factor model. This robustness means my analysis captures the vital elements influencing how AI affects peer-to-peer learning.

In this section, where I discuss the variables' commonalities, I show that the factors extracted in my factor analysis account for much of each variable's variance. High extraction communalities suggest that the factors identified effectively capture a significant portion of the variability in student responses about online learning, which is crucial for understanding AI's role in learning and teaching.

4.4.4.3 Considerations

While high commonalities are reasonable, it is necessary to remember that they do not guarantee the factors are the most meaningful or the only influences. They suggest that the factors I have identified are significant in explaining the variance in my specific variables. For variables with lower commonalities (like .613 for "Should there be a greater use of online learnings"), other factors not identified in my analysis also play a role.

4.4.5 Total Variances

In the context of this study, the Total Variance Explained section of the factor analysis, shown in Table 4-11, offers meaningful variability in the data that is considered valuable.

Table 4-11 Total Variances

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.988	74.710	74.710	2.988	74.710	74.710
2	.490	12.261	86.971			
3	.382	9.561	96.532			
4	.139	3.468	100.000			
Extraction Method: Principal Component Analysis.						

Table 4-11 tabulates the overall variability in the data. The factors identified in the analysis explain variability. This section outlines the meaning of each component, where each factor represents a specific aspect or dimension of the data.

4.4.5.1 Initial Eigenvalues

Initial eigenvalues comprise three sets of values given as:

- Total – this number represents the variance each component (factor) accounts for before extraction. For example, the first component has an initial eigenvalue of 2.988.

- % of Variance – this percentage shows how much of the total variance in the data is accounted for by each component. In this case, the first component explains 74.710% of the variance.
- Cumulative % increases the variance explained as one moves through the components. It shows how much of the total variance is defined by all the elements up to that point.

4.4.5.2 After factor extraction

The extraction total is a single value in Table 4-9 as 2.988. This aspect of Table 4-9 comprises two sets of values, namely:

- % of Variance is the percentage of variance explained by each component after extraction. For the first component, it's still 74.710%.
- Cumulative % is the total percentage of variance explained by all components extracted so far. The first component alone accounts for 74.710% of the variance.

The following items demonstrate the relevance of this analysis for the study:

- Dominant factor – the first component is particularly prevalent, explaining a significant portion (74.710%) of the variance. This component suggests that this factor is pivotal in understanding how AI facilitates peer-to-peer learning.
- Contributions of other factors – the remaining components (2, 3, and 4) explain smaller portions of the variance (12.261%, 9.561%, and 3.468%, respectively). Though less dominant, these factors still contribute to understanding different dimensions of your research.
- Comprehensive understanding – the cumulative percentage reaching 100% with the four components indicates that these factors fully account for the variability in the dataset. This complete understanding is crucial for a nuanced view of AI's role in peer-to-peer learning.

The Total Variance section in Table 4-11 of the factor analysis is central to understanding the significance and impact of different factors identified in the study.

The first component explains a significant portion (74.710%) of the variance, suggesting it is necessary to understand how AI facilitates peer-to-peer learning. The cumulative percentage reaching 100% indicates that these factors fully account for the variability in the dataset. In summary, this part of the analysis helps us to understand the importance and impact of different factors (components) identified in the study, showing how each contributes to the overall understanding of AI in the context of peer-to-peer learning.

4.4.6 Component Matrix

The Component Matrix - Table 4-12 - from my factor analysis provides meaningful insights.

Table 4-12 Component Matrix

Component Matrix[a]	
	Component
	1
Are online classes easily accessible via Blackboard?	.914
Have you attended online classes in the last four weeks?	.912
If you have not attended online classes, why not?	.841
Should there be greater use of online learning	.783
Extraction Method: Principal Component Analysis.	
a. one component extracted.	

This matrix shows how each variable (question from my survey) relates to the identified factor(s). Here is a breakdown:

4.4.6.1 Component section of the matrix

The component section refers to the factor or underlying theme extracted from the data. This study has removed only one component (or factor). Table 4-12 reflects the following data:

- The numbers (.914, .912, .841, .783) are called 'loadings' and represent how strongly each variable is associated with the extracted component.

- A higher loading (closer to 1) means the variable is more strongly related to the component. For instance, "Are online classes easily accessible via blackboard?" with a loading of .914 is highly associated with this component.

4.4.6.2 Interpretation

The high loadings of these questions signify their strong connection to the key factor identified in my analysis, which linked the relevance of the questions. This loading implies the presence of a dominant theme or aspect within my data concerning the influence of AI on peer-to-peer support for learning. Concepts to consider include:

- Understanding the component – given the substantial loadings on this single component, it may represent 'accessibility and engagement in online learning.' It encompasses aspects such as ease of access, usage patterns, reasons for non-participation, and attitudes towards increased online learning.
- The focus of analysis – the presence of a dominant component prompts my analysis to concentrate on understanding how this overarching factor impacts peer-to-peer learning facilitated by AI. This component focuses on investigating the functions of accessibility, engagement, and attitudes regarding online learning environments.

4.4.6.3 Implications

The Component Matrix highlights several implications. These include:

- Comprehensive view – this investigation offers a wide-ranging viewpoint on a noteworthy factor influencing AI in peer-to-peer learning.
- The basis for suggestions – the high loadings highlight the key features of student participation and engagement in AI platform learning environments and are recommendations for improving AI-based learning environments.

The Component Matrix provides insights into how each variable relates to the identified factor(s). The study extracted only one component, with the loadings showing solid associations between specific questions and this dominant factor. The component suggests the factor is 'accessibility and engagement in online learning.' It highlights exploring accessibility, engagement, and attitudes towards online learning platforms. This component is crucial in the context of AI and peer-to-peer learning.

The Component Matrix of the analysis identified significant components: participation, ease of use, barriers to attendance, and perception towards online learning.

4.4.7 Rotated Component Matrix

The perception components towards online learning and AI peer-to-peer support are statistically analysed and limited to one, as shown below in Table 4-13, making this analysis not applicable.

- One component extracted: My analysis resulted in only one factor from the data, suggesting that one theme or pattern can explain most variability.
- No rotation is possible: Since there's only one component, there's nothing to rotate. Rotation makes sense when there are multiple factors, as it helps to differentiate them more clearly. But with just one factor, this step isn't applicable.

Table 4-13 Rotated Component Matrix

Rotated Component Matrix[a]
a. The analysis yielded only one factor, which precluded the rotation of the solution.

Implications emanating from the rotated component matrix include:

- Dominant factor – extracting only one component suggests a robust and dominant theme regarding AI and peer-to-peer learning in my data. This factor captures the most significant pattern or influence in the dataset.
- Understanding and application – this single factor represents a pivotal aspect of AI's role in peer-to-peer learning. Depending on the variables, it could be related to aspects like ease of use, engagement, or effectiveness.

The extraction of only one component and the inability to perform rotation reveal a simplified yet strong pattern in the data. Since my study extracted only one component, rotation proved unnecessary. This component indicates a dominant and simplified pattern related to AI's role in peer-to-peer learning.

In conclusion, my study has indicated a correlation between the variables reconsidering the use of AI in peer-to-peer support as a learning tool. Elements such as availability and participation help to explain this concept. These findings support AI as a tool for enabling peer-to-peer learning support.

4.4.8 Descriptives

Table 4-14 describes the distribution and characteristics of responses for the main factor (aspect) measured in the surveys.

Table 4-14 Descriptives

			Statistic	Std. Error
Factor	Mean		3.91	.057
	95% Confidence Interval for Mean	Lower Bound	3.80	
		Upper Bound	4.02	
	5% Trimmed Mean		3.98	
	Median		3.67	
	Variance		.770	
	Std. Deviation		.877	
	Minimum		1	
	Maximum		5	
	Range		4	
	Interquartile Range		1	
	Skewness		-.940	.158
	Kurtosis		1.362	.316

A discussion of the values set out in Table 4-14 is listed below:

- Mean (3.91): Average responses to the survey questions score around 3.91 (scale used, 1-5).
- Standard Error (0.057): A more minor standard error suggests a more precise estimate.
- 95% Confidence Interval for Mean: The population's true mean is likely between 3.80 and 4.02. This range gives an idea of the precision of the mean estimate.

- 5% Trimmed Mean (3.98): This is the mean calculated after trimming 5% of the extreme values from either end of the range. It's a measure that's less affected by outliers.
- Median (3.67): Half of the responses are above this value, and half are below. It's another measure of central tendency.
- Variance (0.770) and Standard Deviation (0.877): These measure the spread or variability of my data. They tell how much responses vary from the mean.
- Minimum and Maximum: The lowest and highest values in the responses (1 and 5) indicate the responses' range.
- Range (4) and Interquartile Range (1): The range shows the difference between the lowest and highest responses. The interquartile range offers the spread in the middle 50% of the data.
- Skewness (-0.940): Indicates the asymmetry of the response distribution. Negative skewness suggests a tail on the left side.
- Kurtosis (1.362): Positive kurtosis indicates whether the data are peaked or flat relative to a normal distribution, suggesting a distribution with more peaks.
- The descriptive statistics summarise the survey data related to the main factor, suggesting a reliable and precise measure. The skewness coefficient is slightly negative, meaning that most of the responses are above the scale's mid-point, while kurtosis is positive, meaning that the distribution is peaked. These statistics are crucial for understanding the survey data's central tendency, variability, and distribution shape.

Several implications emerge from the values set out in Table 4-14. The mean (3.91) and the median (3.67) also suggest that participants had a positive attitude towards the survey questions, and the range was from 1 to 5. The relatively narrow 95% confidence interval (3.80-4.02) suggests that the sampling mean is reasonably accuracy, and the standard error is relatively low at 0.057. The 5% trimmed mean (3. 98) indicates that outliers do not significantly impact the data. The variance (0. 770) and standard deviation (0. 877) are relatively low, indicating moderate response variation. The negative skewness coefficient (-0.940) suggests that the responses skew slightly toward the higher end of the scale. In contrast, the kurtosis coefficient is positive (1. 362), indicating a more peaked distribution of the responses. These statistics collectively mean that the data is credible and accurate, thus backing the study's findings regarding the use of AI in peer-to-peer learning by giving a thorough account of response patterns and distribution forms.

In the final analysis, validating the statistics shows that the surveys are a trustworthy method for gauging important components of AI in peer-to-peer learning environments, which is central to the validity of my findings. The final analysis involves statistically validating the data.

4.4.9 Validated Statistics

Table 4-15 validates and summarises the survey findings and implications of the various statistical analyses, followed by a narrative discussion.

Table 4-15 Summary of Results

Section	Key Findings and Implications
Correlation Matrix	Variables related to AI in peer-to-peer learning are correlated (0.078 det.)
KMO and Bartlett's Test	High extraction communalities indicate factors that capture variability. Bartlett's Test confirms significant correlations among variables.
Commonalities	High extraction communalities indicate factors that capture variability.
Total Variances	The first component (74.710%) is significant in AI and peer-to-peer learning.
Component Matrix	The dominant component represents 'accessibility and engagement in online learning.' Emphasises the importance of exploring accessibility, engagement, and attitudes.
Rotated Component	A single dominant factor simplifies the pattern related to AI and peer-to-peer learning.

The correlation matrix reveals that the variables related to AI in peer-to-peer learning are not independent, with the determinant being 0. 078, which hints at structural integration. KMO and Bartlett's Test results showed that the extraction of factors was high, indicating that the variables are related and thus appropriate for factor analysis. The similarities suggest that the listed factors adequately explain the variability of the data. The total variances show that the first component, which accounts for 74. 710% of the variance is vital in explaining how AI fits into the context of peer-to-peer learning. The component matrix reveals that the dominant components are accessibility and engagement in online education, as seen in the table. Thus, the rotated component analysis indicates that one, maybe two, significant factors connect AI and peer-to-peer learning, making the results easier to comprehend and apply.

4.4.10 Reliability

This reliability section assesses how consistently my archival survey measures what it intends to measure. The eSonga repository stores the raw survey data Figshare. https://figshare.com/s/1f6173c54222ce2d4705 (Wilson-Trollip, 2024).

Table 4-16 Case Processing Summary - Reliability

Case Processing Summary			
		N	%
Cases	Valid	109	46.2
	Excluded[a]	127	53.8
	Total	236	100.0
[a]All variables in the procedure are based on Listwise deletion.			

This case processing summary in Table 4-16 provides information on the data used for the reliability analysis, set out as follows:

- Valid cases (109, 46.2%) – this was the number and percentage of survey responses used in the analysis.
- Excluded cases (127, 53.8%) – I excluded these responses because they had incomplete answers or missing data.
- Total (236, 100%) – the total number of cases (responses) considered.
- The analysis included 109 valid cases, representing 46.2% of the survey responses.

Effectively, this means that out of 236 total survey responses, only 109 were complete and usable for the analysis, constituting 46.2% of the data. The remaining 127 responses, making up 53.8%, were excluded due to incomplete or missing information. This exclusion rate indicates a portion of the data was unusable, which could impact the robustness and representativeness of the study's findings.

Table 4-17 presents the reliability statistics of the survey, which is significant when assessing the consistency of the measurement tool used in the study. Cronbach's Alpha ($\alpha = .876$) is a crucial statistic for reliability, with higher values indicating excellent reliability. A value of .876 demonstrates remarkable consistency, implying that the survey items (questions) consistently measure the same underlying concept. N represents the number of items (4) assessed for reliability in the survey.

Table 4-17 Reliability Statistics

Reliability Statistics	
Cronbach's Alpha	**N of Items**
.876	4

Table 4-18 evaluates each survey question individually. Aspects assessed include:

- Scale Mean if Item Deleted: This calculation assesses each item's impact on the overall scale, revealing the average score when removing one item.
- Scale Variance if Item Deleted: This addresses the question, “How much does removing an item change the variance (spread of scores)?”
- Corrected Item-Total Correlation: This shows how well each item correlates with the total score of the other items. Higher correlations indicate that the item fits well with the overall scale.
- Cronbach's Alpha if Item Deleted: This shows what Cronbach's Alpha would be if one removed that item. It suggests the item might not fit well with others. The high Cronbach's Alpha indicates that my survey is reliable for measuring whatever aspect of AI and peer-to-peer learning I focus on.

Table 4-18 Item-Total Statistics

Item-Total Statistics				
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**
Are online classes easily accessible via Blackboard?	13.27	6.456	.813	.815
Have you attended online classes in the last four weeks?	13.20	6.607	.811	.819
If you have not attended online classes, why not?	13.59	6.059	.715	.852
Should there be greater use of online learning	13.53	6.233	.643	.884

The final analysis involves thematically analysing grades and pass rates and validating these findings with a t-test to determine any changes in grades and pass rates resulting from the intervention. Similarly, to determine what students believe the effect of the platform has on their grades.

4.4.11 Summary

The descriptive statistical analysis shows the correlation and the strength of the variables associated with AI in peer-to-peer learning. The determinant value of the correlation matrix is 0.078, meaning that the variables are not entirely orthogonal, implying a correlation between the ease of using the AI platform and the usefulness of the content provided. The Kaiser-Meyer-Olkin Measure of 0.789 also supports the appropriateness of performing factor analysis on the data, and Bartlett's Test of Sphericity with a Chi-Square value of 270.307, and a significance level of less than 0.001 supports the existence of the relationships between the variables. The commonalities show that the extracted factors account for a large proportion of the variance in the students' responses, with high extraction communalities signifying these factors are crucial in accounting for the variance in the variables. The Total Variance Explained section shows that the first component captures 74.710% of the total variance, underscoring its importance in explaining how AI supports peer learning. The Component Matrix reveals a high correlation between specific questions and the dominant factor, which suggests that accessibility and engagement play a role in online learning. Extraction of only one component made rotation unnecessary, simplifying interpretation and underscoring the primary influence of AI on peer-to-peer support platform learning.

The descriptive statistics give a clear picture of the data collected from the survey, with a mean response of 3.91 and a median of 3.67, a relatively positive score. The narrow 95% confidence interval and the low standard error show that the estimates are accurate and consistent. At the same time, the negative skewness and positive kurtosis indicate that the data distribution is slightly skewed and leptokurtic. The reliability analysis showed a Cronbach's Alpha of 0.876, revealing good survey item reliability. Among the 236 participants, only 109 had provided valid responses, making it 46.2% of the data, with 53.8% excluded because of missing data.

In conclusion, the analysis reveals high correlations between variables and data reliability, supporting the relevance of accessibility and engagement in AI-mediated online learning environments, which can help inform the improvement of educational practices with the help of AI technologies.

4.5 Grades and Pass Rates

The final thematic analysis and statistical investigation are required to determine whether AI as peer-to-peer support can enhance academic grade performance. Student final grade achievement and pass rates are measures of academic grade performance for this study. Performance may include other factors, like attitudes, which link to young people's intentions and are subsequently associated with performance behaviour. Research indicates that individualised instruction can improve learning outcomes, grades, and higher retention rates. Leveraging AI as student peers in learning and teaching have faced implementation challenges in promoting a learning culture and the Student Learning Models (SLM), which seek to personalise learning, making it unique and responsive to the student. Integrating AI to realise how it can formulate individualised instruction for large groups of students remains vital. Hence, understanding what students perceive to be the influence of AI as a peer-to-peer support tool on their grades is assessed.

4.5.1 Population and Sample

The study included data on grades from 19 distinct courses, covering a population of 4363 enrolled learners. The sample size for each class varied from 1 to 240. Notably, one should acknowledge the data's institution-specific nature, which may preclude generalisation to the entire learner population of other universities. Annexure 4 illustrates one dataset of 19 accessed from the institutions' official grade archives.

The sample size, comprising 4363 grades as shown in Appendix 6 (A), is adequate for validating the groups outlined in Pre-Intervention N = 2226 and Post-Intervention N = 2137, as illustrated in Figure 4-4, Figure 4-5, and Figure 4-6. Table 4-17 shows the distribution of these enrolments, grades and pass rates in evaluating platform efficacy regarding performance. The sample size surpassed the recommended threshold of 100 to 200 respondents Spector (1992) and was considered substantial, with over 500 respondents (Bermudez, 2023). The construct consisted of four groups, Financial Management 1 to 4, as illustrated in Table 4-19.

Table 4-19 Learner Enrolment Figures 2017-2022

Row Labels	**Sum of Enrolments**	**Sum of Passed**	**Average Pass Rate**	**Average Final Mark**
2017	836	656	78.69%	59.36%
2018	698	554	79.91%	56.17%
2019	692	504	74.08%	54.20%
2020	692	553	83.46%	58.41%
2021	694	537	81.49%	57.93%
2022	751	587	83.77%	61.22%
Grand Total	4363	3391	80.5%	58.0%
Pre-Intervention				
Row Labels	**Sum of Enrolments**	**Sum of Passed**	**Average Pass Rate**	**Average Final Mark**
2017	836	656	78.69%	59.36%
2018	698	554	79.91%	56.17%
2019	692	504	74.08%	54.20%

Grand Total	2226	1714	77.0%	56.6%
Post-Intervention				
Row Labels	**Sum of Enrolments**	**Sum of Passed**	**Average Pass Rate**	**Average Final Mark**
2020	692	553	83.46%	58.41%
2021	694	537	81.49%	57.93%
2022	751	587	83.77%	61.22%
Grand Total	2137	1677	78.5%	59.2%

The course data categorises enrolments, pass rates, and average final marks. These categories, consisting of multiple related components or constructs, measure different aspects of learner performance.

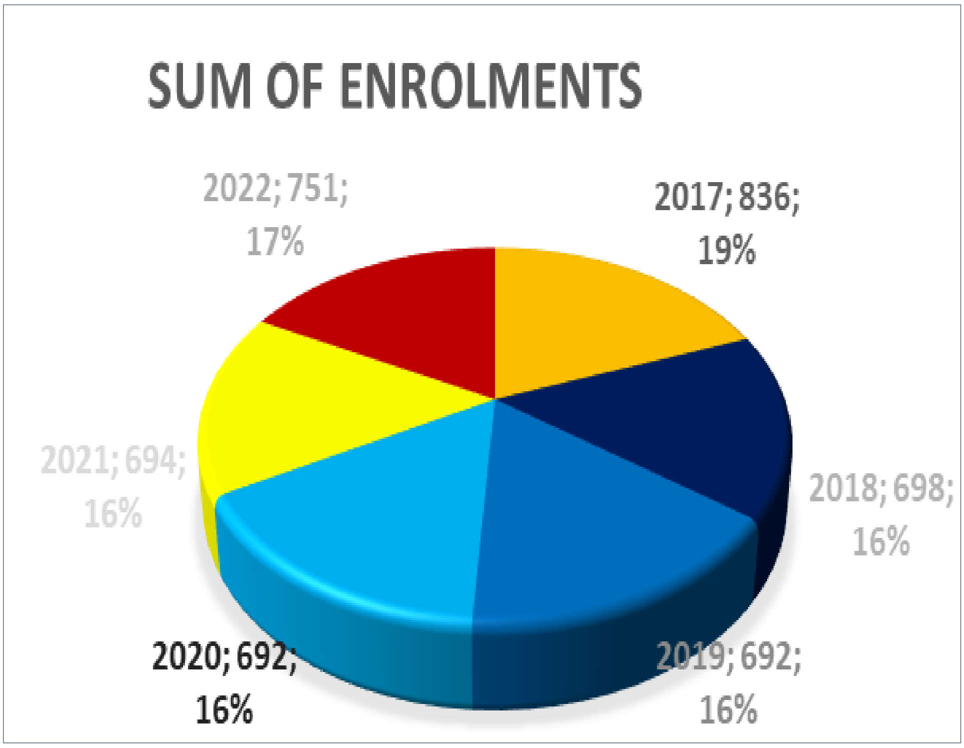

Figure 4-4 Total Enrolment Figures by Year: 2017-2022

The pie chart titled Sum of Enrolments, Figure 4-5, shows the enrolment of students for six years from 2017 to 2022. The table shows that enrollment was highest in 2017 at 836 (19%). The enrollments in 2018, 2019 and 2020 were also quite comparable, each contributing 16% to the total, with 688, 692 and 692 enrolling, respectively. In 2021, enrolments rose marginally to 694 while still capturing a 16% market share. In 2022, there was an increase to 751 enrolments, which was 17%. In summary, the enrolment figures reveal a general downward trend from 2017 to 2020 and a slow upward trend in the subsequent years, suggesting a somewhat volatile but relatively steady trend in student enrolment over the analysed period.

The Pre-Intervention pie chart, Figure 4-6, illustrates student enrolment distribution across three years: 2017, 2018, and 2019. The enrolment rate was highest in 2017, with 836 students, which was 38% of the total pre-intervention enrolments. The number of enrolments in 2018 and 2019 was almost the same, with 698 and 692 learners, respectively, who made up 31% of the total. This data shows that before the intervention, enrolment was high in 2017 and then declined, but it remained relatively constant in the subsequent two years. The enrollment figures for 2018 and 2019 indicate no significant change in the number of students before the intervention.

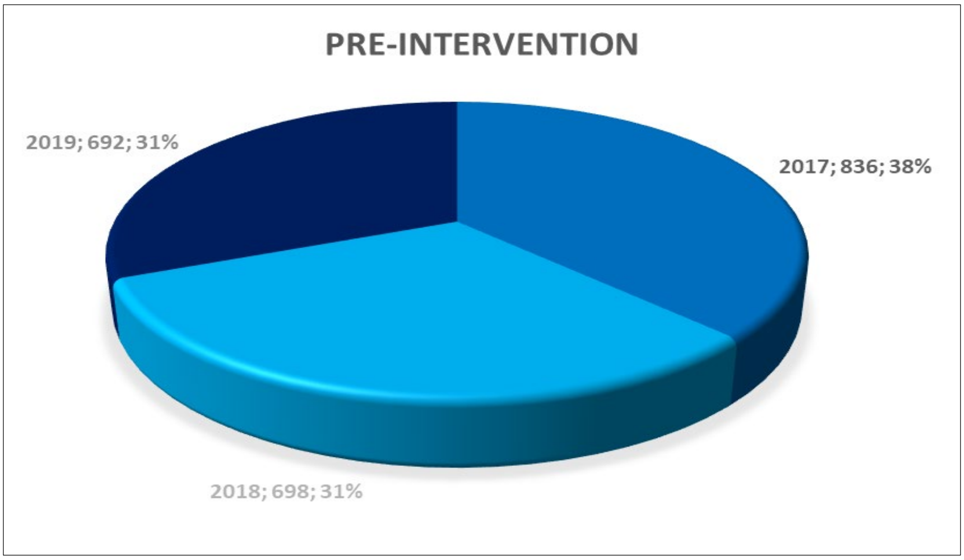

Figure 4-5 Pre-Intervention Enrolment Figures by Year: 2017-2019

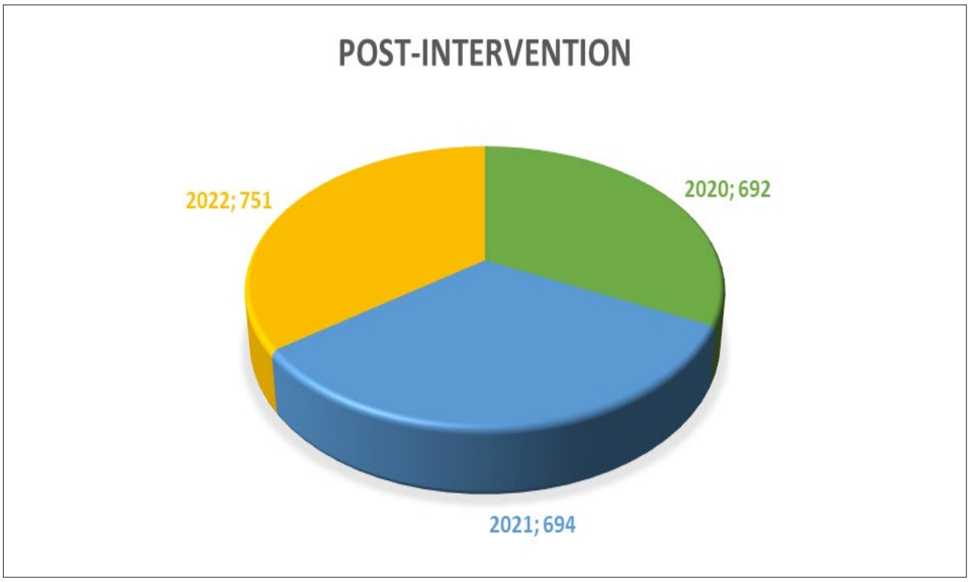

Figure 4-6 Post-Intervention Enrolment Figures Year: 2020-2022

The Post-Intervention pie chart, Figure 4-6, shows student enrolment distribution across 2020, 2021, and 2022. 2020 the enrolment rate was 692, comparable to the previous years before the intervention. In 2021, the enrolment slightly grew to 694. The most drastic shift was observed in 2022 when the enrolment increased to 751, contributing to the post-intervention figure. This rise implies a positive change in student enrollment after the intervention, meaning that the measures taken may have helped enrol or retain students. The data indicates steady trends in enrolment in the years immediately following the intervention and a sharp increase in the third year.

4.5.2 Descriptives

The data details students' enrollment, pass rate, and average final grades. The categorisation divides the information into four sections: Average Final Mark, Passed, Enrolments, and Pass Rate. The analysis seeks to determine if the AI peer-to-peer support platform influences student grades and pass rates, and if so, how.

These factors provide insights into the performance and outcomes of the learners, as illustrated in Table 4-20.

Table 4-20 Descriptive Metrics for Grades and Pass Rates

Enrolments		*Passed*		*Pass Rate*		*Average Final Mark*	
Mean	161,5925926	Mean	125,5925926	Mean	0,805291992	Mean	0,580285802
Standard Error	16,22212791	Standard Error	11,85275994	Standard Error	0,018914421	Standard Error	0,014433024
Median	191	Median	146	Median	0,816831683	Median	0,5751
Mode	#N/A	Mode	146	Mode	#N/A	Mode	#N/A
Standard Deviation	84,29264922	Standard Deviation	61,58874726	Standard Deviation	0,098282216	Standard Deviation	0,074996195
Sample Variance	7105,250712	Sample Variance	3793,173789	Sample Variance	0,009659394	Sample Variance	0,005624429
Kurtosis	-1,198073241	Kurtosis	-1,138218516	Kurtosis	-0,793227276	Kurtosis	1,281079726
Skewness	-0,319544247	Skewness	-0,417536836	Skewness	0,223653197	Skewness	1,289803943
Range	273	Range	208	Range	0,335189573	Range	0,28855
Minimum	20	Minimum	19	Minimum	0,639810427	Minimum	0,47095
Maximum	293	Maximum	227	Maximum	0,975	Maximum	0,7595
Sum	4363	Sum	3391	Sum	21,74288379	Sum	15,66771667
Count	27	Count	27	Count	27	Count	27
Confidence Level(95.0%)	33,34506147	Confidence Level(95.0%)	24,36369698	Confidence Level(95.0%)	0,03887915	Confidence Level(95.0%)	0,029667507

The descriptive metrics findings linked to grades and pass rates were as follows:

- Enrolments – on average, there were 161.6 enrolments with a significant standard deviation of 84.29, indicating wide variation. The median was 191. The enrolments ranged from 20 to 293, with a total sum of 4,363 across 27 counts.
- Passed – the average number of individuals who passed was 125.6. Again, a large standard deviation of 61.59 suggests significant variability. The median number of passes was 146, with a range of 208. The total sum of passes was 3,391.
- Pass Rate – the mean pass rate stood at 0.805, with a standard error of 0.019, indicating a consistent pass rate across the sample. The median pass rate was slightly higher at 0.817, ranging from 0.64 to 0.975. This median pass rate suggests that in the COVID-19 period, there was no statistically significant decrease in the pass rates.
- Average Final Mark – the mean final mark was 0.580, with a standard error of 0.014. The median was close to the mean at 0.575, suggesting a symmetric data distribution around the centre. The range of final marks was 0.289, with values between 0.471 and 0.760. This mean final mark indicates that in the COVID-19 period, there was no statistically significant decrease in the final marks.
- Variability and Distribution – The enrollments and passed data show negative kurtosis, indicating a flatter distribution than the normal distribution, with fewer outliers. Pass rate and average final mark data exhibit positive skewness, particularly the last marks,

suggesting that more students received marks on the lower end of the scale.

- Confidence Levels – the 95% confidence level for enrolments and passed suggests that the estimated mean of these populations is within +/- 33.35 and +/- 24.36 of the sample mean, respectively. The confidence intervals are much smaller for pass rates and average final marks, indicating a higher precision of the mean estimate.

The grade descriptive metrics findings reveal several vital insights. On average, there were 161.6 enrolments per course, with a significant standard deviation of 84.29, indicating wide variation among courses. The median enrolment was 191, ranging from 20 to 293 and 4,363 enrolments across 27 courses. The average number of individuals who passed was 125.6, with a large standard deviation of 61.59, suggesting significant variability. The median number of passes was 146, ranging from 20 to 228, totalling 3,391. The mean pass rate stood at 0.805, with a low standard error of 0.019, indicating consistency across the sample. The median pass rate was slightly higher at 0.817, ranging from 0.64 to 0.975, suggesting that pass rates did not significantly change during the period. The mean final mark was 0.580, with a standard error of 0.014. The median final mark was close to the mean at 0.575, indicating a symmetric distribution. Final marks ranged from 0.471 to 0.760, suggesting that final marks also did not significantly change. The enrolments and passed data exhibited negative kurtosis, indicating a flatter distribution with fewer outliers than a normal distribution. The pass rate and average final mark data showed positive skewness, particularly for the final marks, suggesting that more students received marks on the lower end of the scale. These metrics provide a comprehensive view of student performance during the study period, highlighting consistency in pass rates and final marks despite the challenges posed by events, notably the COVID-19 pandemic.

Table 4-21 summarises the pre and post-intervention pass rates and final average marks per course, Financial Management 1, 2,3 and 4.

Table 4-21 Financial Management Enrolments, Pass Rates and Grades

Group: Financial Management 1

Year	Enrolments	Passed	Pass Rates	Average Final Grades
Pre-intervention				
2017	289	201	69.55%	62.15%

Year	Enrolments	Passed	Pass Rates	Average Final Grades
Pre-intervention				
2018	190	146	76.84%	58.75%
2019	211	135	63.98%	50.74%
Post-intervention				
2020	213	154	72.30%	50.10%
2021	242	158	65.29%	53.31%
2022	293	198	67.58%	51.71%

Group: Financial Management 2

Year	Enrolments	Passed	Pass Rates	Average Final Grades
Pre-intervention				
2017	271	227	83.76%	58.31%
2018	218	161	73.85%	54.53%
2019	227	163	71.81%	53.44%
Post-intervention				
2020	192	141	73.44%	53.71%
2021	208	152	73.08%	47.10%
2022	191	140	73.30%	52.86%

Group: Financial Management 3

Year	Enrolments	Passed	Pass Rates	Average Final Grades
Pre-intervention				
2017	196	167	85.20%	59.46%
2018	236	202	85.59%	58.44%
2019	202	165	81.86%	60.91%
Post-intervention				
2020	186	170	91.40%	58.03%
2021	154	150	97.40%	75.00%
2022	150	146	97.33%	75.95%

Group: Financial Management 4

Year	Enrolments	Passed	Pass Rates	Average Final Grades
Pre-intervention				
2017	80	61	76.25%	57.51%
2018	54	45	83.33%	52.98%
2019	52	41	78.85%	51.71%
Post-intervention				
2020	81	69	85.19%	55.18%
2021	60	51	85.00%	56.33%
2022	77	64	83.12%	58.52%

The data analysis for Financial Management courses pre- and post-intervention reveals distinct enrollment trends, pass rates, and average final grades. The outcomes of the data analysis are:

- For Financial Management 1 – enrolments increased post-intervention, peaking at 293 in 2022. The pass rates and average final grades, however, displayed inconsistency. The pass rate rose from 63.98% in 2019 to 72.30% in 2020 but fell to 65.29% in 2021 before slightly recovering to 67.58% in 2022. Average final grades remained relatively low, with minimal improvement from 50.10% in 2020 to 51.71% in 2022.
- Financial Management 2 – showed a decline in pass rates and average final grades pre-intervention, with pass rates falling from 83.76% in 2017 to 71.81% in 2019 and grades dropping from 58.31% to 53.44%. Post-intervention, the pass rates stabilised around 73%, but the average final grades fluctuated, reaching a low of 47.10% in 2021 before slightly recovering to 52.86% in 2022.
- Financial Management 3 – pre-intervention pass rates and grades were already high, with pass rates around 85% and grades around 59%. Post-intervention, pass rates

soared to 97.40% in 2021 and 2022, with average final grades significantly increasing to 75.95% in 2022, indicating a marked improvement in student performance.

- Financial Management 4 – enrolments varied pre-intervention, peaking at 81 in 2020, with pass rates and average final grades improving post-intervention. The pass rate increased from 76.25% in 2017 to 85.19% in 2020, with average grades improving from 57.51% to 58.52% by 2022.

Overall, the data suggests that the intervention had a varied impact across different course levels. Financial Management 3 experienced the most significant positive changes in pass rates and final grades, while Financial Management 4 also showed improvement. Financial Management 2 and 1 had more fluctuating results, with Financial Management 1 showing some enrolment recovery but inconsistent pass rates and grades. Judging by the improvements in the questionnaire, the intervention seems to have had the most significant impact on higher-level courses, namely Financial Management 3 and 4. These findings reveal the character of performance of each group by comparing their dispersion of the enrolments, the pass rates and the average final grades over the year. No values are missing.

Post-intervention measures for the Financial Management 3 and 4 courses show improved pass rates and higher average final marks, indicating the intervention's positive impact. On the other hand, the other two Financial Management courses denoted slightly more significant improvements in the pass rates and relatively stable final grade averages that did not indicate significant changes. The differences in scores at the end of the course highlight the variation in the effectiveness of the intervention at the course's different levels. Altogether, the given information provides some insights into the enrolment, the rate of passes, and the average final marks of a group of learners. Analysing these factors provides insights into the performance and outcomes of the learners, allowing for further exploration and understanding of the dataset.

The data presents pass rates and average final marks for Financial Management courses (1 to 4) over six years. As pointed out from the pie chart, before the intervention (2017-2019), pass rates of Financial Management 1 and 2, as well as average marks, were volatile, but they have proven to be more stable in terms of pass rates and average marks in the post-intervention period (2020-2022). On the other hand, due to the interventional measures recounted above, Financial Management 3 and 4 have risen considerably.

Specifically, Financial Management 3 shows the most significant improvement. The pass rate jumps from 81%-85% pre-intervention to over 91% post-intervention, with average marks increasing from around 60% to over 75%. Financial Management 4 also shows an improvement post-intervention, with pass rates increasing from the mid-70s to over 83% and average marks seeing a modest rise.

The intervention has impacted pass rates and average final marks, particularly in the higher-level courses (3 and 4). The data suggests a correlation between the intervention and improved academic performance, especially in advanced classes.

4.5.3 Grades

Figure 4-7 illustrates the perceptive thematic findings of students' belief that the AI peer-to-peer support platform affects their grades.

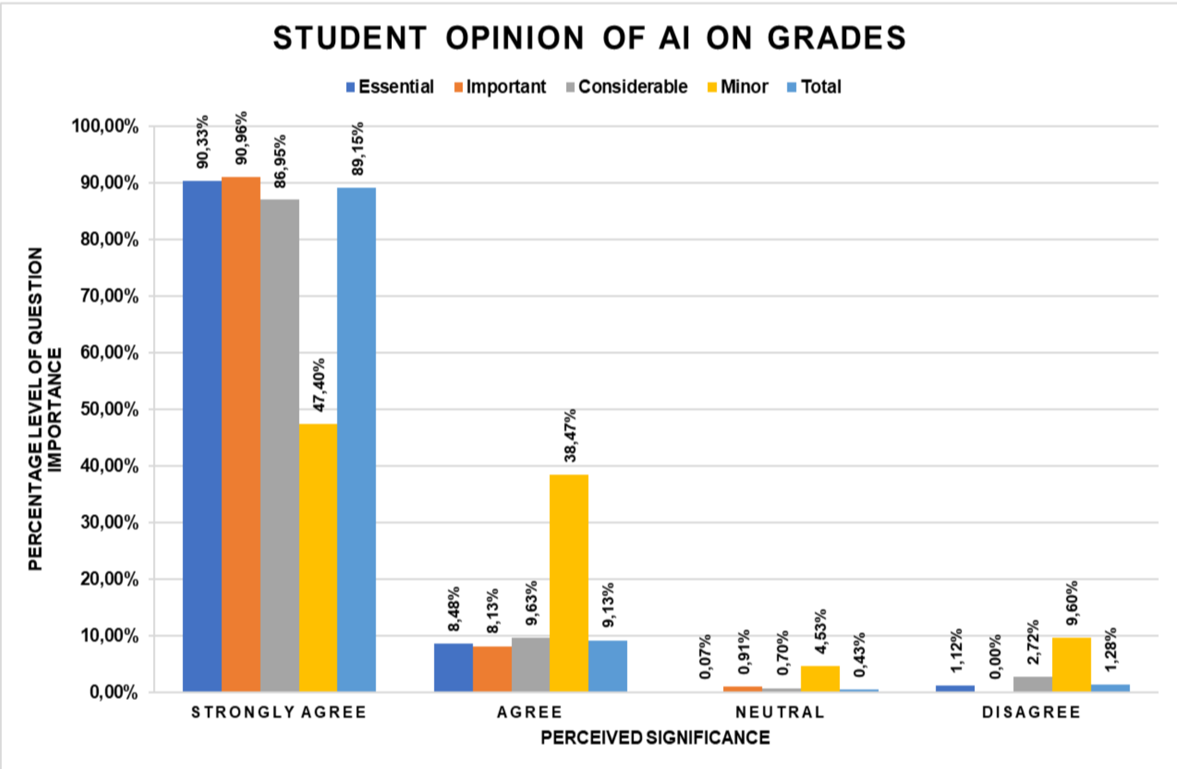

Figure 4-7 Student Opinion of AI on Grades and Pass Rates

Table 4-22 Student Opinion of AI on Grades and Pass Rates

	Strongly Agree	% of Total	Agree	% of Total	Neutral	% of Total	Disagree	% of Total	Total	Sum % of Total
Essential	20.58%	90.33%	1.93%	8.48%	0.02%	0.07%	0.26%	1.12%	22.78%	100.00%
Important	7.46%	90.96%	0.67%	8.13%	0.07%	0.91%	0.00%	0.00%	8.20%	100.00%
Considerable	5.15%	86.95%	0.57%	9.63%	0.04%	0.70%	0.16%	2.72%	5.92%	100.00%
Minor	0.32%	47.40%	0.26%	36.47%	0.03%	4.53%	0.07%	9.60%	0.68%	100.00%
Total	**33.51%**	**89.15%**	**3.43%**	**9.13%**	**0.16%**	**0.43%**	**0.48%**	**1.28%**	**37.59%**	**100.00%**

Table 4-22 presents students' perceptions of how an AI platform influences their grades. The responses are categorised into four levels of agreement: Strongly Agree, Agree, Neutral, and Disagree. The questions were subdivided into Essential, Important, Considerable, and Minor to add to the significance of the results.

Most students, particularly those who view the AI platform as Essential and Important, strongly agree with its perceived improved impact on their grades. Specifically, 90.33% consider it Essential, 90.96% Important, 86.95% Considerable, and 47.40% Minor. This perception demonstrates a strong consensus among students regarding the platform's role in enhancing academic performance.

In the Agree category, the support remains robust but lower than the Strongly Agree category. Here, 8.48% of students consider the platform Essential, 8.13% Important, 9.63% Considerable, and 38.47% Minor. This support indicates that while some students recognise the platform's positive impact, they may not consider it vitally important.

The Neutral responses are minimal, with only 0.43% in total, suggesting that most students have a clear opinion on the AI platform's influence on their grades. The breakdown shows 0.07% for Essential, 0.91% for Important, 0.70% for Considerable, and 4.53% for Minor.

The Disagree category contains the lowest percentages, indicating minimal opposition. No students disagreed with the platform being Important, while 1.12% viewed it as Essential, 2.72% as Considerable, and 9.60% as Minor.

Overall, the data highlights a robust reception toward the AI platform's impact on grades, with most students recognising its necessary role in academic performance. The minimal neutral and disagreement responses further underscore the platform's perceived value among students in enhancing their grades. Further statistical analysis of the data is necessary to determine if the perceived positive influence of the AI platform on engagement affects grades similarly in the eyes of the students. This further statistical analysis applied the two paired t-tests, assuming unequal variances.

Table 4-23 Summary of all courses Grades pre- and post-intervention

Two-tailed T-Test results for Grades 2017 - 2022							
	Pre-Intervention		Post-Intervention				
Subject	Mean	Variance	Mean	Variance	t-value	df	p-value
All the courses for 2017–2022.	0,56283	0,00244106	0,542228571	0,01440785	0,891756747	49	0,37688163
Financial Management 4	0,57862308	0,0016908	0,528996	0,01440647	1,867316163	33	0,07076157
Financial Management 3	0,57973846	0,00174558	0,547048	0,01867359	1,101232858	31	0,2792727
Financial Management 2	0,57039333	0,00238067	0,543457692	0,01800199	0,923289786	35	0,36217788
Financial Management 1	0,5555375	0,00278156	0,547203846	0,0171799	0,288464794	36	0,77464543

It compares average grades and pass rates between pre-and post-intervention categories. Each course's grades are statistically analysed, comparing pre- and post-platform implementation. Table 4-23 presents the four-course t-test analysis of average grades pre-and post-intervention.

The data shown represents t-test statistics for average course grades, comparing pre- and post-intervention grade values. Here is a summarised interpretation:

To analyse the t-test data, extracted and interpreted provide the fundamental values, given as:

- T-Value – this is the calculated value from the t-test formula. It indicates the difference between the two groups' means relative to the variability observed within the groups.
- Df (degrees of freedom) represents the number of independent values or quantities that can vary in the analysis.
- Sig. (2-tailed) – this is the p-value associated with the t-test. It indicates the probability that the observed differences occurred by chance. A p-value less than 0.05 is typically considered statistically significant.
- Mean Difference – this is the difference in means between the two groups.
- Standard Error Difference – this is the standard error of the mean difference. It measures the accuracy with which the sample mean difference estimates the

population mean difference.

- Confidence Interval of the Difference (95% CI) – this range contains the actual mean difference with 95% confidence. If this interval does not include zero, the difference is statistically significant.

Table 4-23 presents the results of a two-tailed T-test comparing pre-intervention and post-intervention grades for four financial management courses from 2017 to 2022. The analysis includes the mean and variance of grades, t-values, degrees of freedom (df), p-values for each course, and an aggregate of all classes.

For all courses combined over the five years, the mean grade decreased slightly from 0.56283 (pre-intervention) to 0.54223 (post-intervention). The t-value is 0.8918 with 49 degrees of freedom and a p-value of 0.3769, indicating no statistically significant difference.

Financial Management 1 experienced a slight decrease in mean grade from 0.5555 to 0.5472. The t-value is 0.2885 with 36 degrees of freedom and a p-value of 0.7746, indicating no significant difference.

Financial Management 2 shows a mean grade reduction from 0.5704 to 0.5435. The t-value is 0.9233 with 35 degrees of freedom and a p-value of 0.3622, reflecting no significant difference.

Financial Management 3 also decreased the mean grade from 0.5797 to 0.5470. The t-value is 1.1012 with 31 degrees of freedom and a p-value of 0.2793, indicating no significant change.

In Financial Management 4, the mean grade dropped from 0.5786 to 0.5290, with a t-value of 1.8673 and a p-value of 0.0708 (df = 33), suggesting a marginally significant difference, but not enough to conclude a substantial impact.

Overall, the data suggests that introducing the AI platform did not result in a statistically significant impact on grades across the courses evaluated. The slight reductions in mean grades post-intervention do not reach levels of statistical significance, indicating that while there may be minor variations, these are not substantial enough to attribute to the intervention confidently. This slight effect on the grades statistically differs from the perceived effect that students believed had on the grades.

In conclusion, the intervention did not lead to a statistically significant grade change for any Financial Management courses analysed (Financial Management 1 to 4) or all courses combined from 2017 to 2022. This insignificance means that any observed differences in mean grades before and after the intervention are likely due to random variation rather than the intervention itself. Regarding activity and grades, Figure 4-9 Course Activity Overview and Table 4-22 t-Test: Paired Two Sample for Means Activity and Grades represent an extract and analysis of activity data from a 2022 Financial Management 4 course, also shown in Appendix 6 (N), in the link to the eSonga repository. Figshare. https://figshare.com/s/1f6173c54222ce2d4705 (Wilson-Trollip, 2024). The significance of the data is related to the levels of time spent engaging with a class and the associated performance as a measurement of grades obtained extracted in Figure 4-8.

Course Activity Overview

Course Name	**FINANCIAL MANAGEMENT 4**
Course ID	2022_0_FT_FNM470S
Number of Students	71
Number of Active Students	70
Date Range	31/01/22 - 30/11/22

Activity for all enrolled students.

Course Overview

Student Activity By Day

Charts do not appear in Excel

31/01/22 - 30/11/22

Total Time in Course	3529,27
Average Time Per Active Student	50,42

Day of Week	Hours
Monday	203,38
Tuesday	386,16
Wednesday	509,76
Thursday	647,35
Friday	490,91
Saturday	400,90
Sunday	890,81

Student Overview (71 Students)

Click a bar to view a student's individual activity.

Charts do not appear in Excel

Figure 4-8 Course Activity Overview

Based on this information, correlation and t-test analyses were conducted to provide results by comparing the hours spent with the grades obtained, as shown in Table 4-24. Seventy-one students' grades and activity levels are analysed and correlated.

Table 4-24 t-Test: Paired Two Sample for Means Activity and Grades

	Course Activity in Hours	Grades
Mean	59,67314216	57,03793103
Variance	2013,397912	376,8116062
Observations	58	58
Pearson Correlation	-0,138599745	
Hypothesised Mean Difference	0	
df	57	
t Stat	0,39121448	
P(T<=t) two-tail	0,6970973	
t Critical two-tail	2,002465403	

The T-Test: In the Paired Two Sample for Means Table 4-24, the t-test Compare Course Activity in Hours and Grades describes the result of a packed samples t-test. The analysis of the related statistical outcomes emerges as follows:

- Mean – the average Course Activity in Hours is 59.67, and the average Grade is approximately 57.04. This average suggests a slight mean difference between the two paired samples.
- Variance – there is more variability in Course Activity in Hours (Variance ~2013.40) compared to "Grades" (Variance ~376.81). The variability shows that the spread of hours spent on course activities is wider than the grade distribution.
- Observations – the equal observation count (58) for both variables suggests paired data. Each course activity in hours of observation corresponds to a grade observation for the same student.
- Pearson Correlation - the correlation between the two variables is approximately -0.139, indicating a weak negative linear relationship.

- Hypothesised Mean Difference – the test assumes no difference in the means of the two variables (the null hypothesis).
- Degrees of Freedom (df) – there are 57 degrees of freedom, calculated as the number of observations minus one for a paired t-test.
- t Stat – the t-statistic is 0.391, the calculated value used to evaluate whether the difference between the two-sample means is statistically significant.
- P(T<=t) two-tail – the two-tailed p-value is approximately 0.697. This value assesses statistical significance in both directions. As it exceeds 0.05 significantly, it implies no notable difference between the two means at the 5% significance level in either direction.
- t Critical two-tail – the critical t-value for a two-tailed test is approximately 2.002. Rejection of the null hypothesis, even if applicable, is not an option as the calculated t-stat is lower.

The paired t-test results suggest no statistically significant difference between the mean hours of course activity and grades. The hours spent on the course do not reflect the amount or quality of practice students have with the content. Widely accepted research shows that students learn more with increased practice. Therefore, time spent on the platform may not mean improved grades. However, training, practice and time spent on the platform may improve grades. Despite a slight mean difference, the relationship between these variables is not strong enough to be considered statistically significant.

4.5.4 Pass Rates

T-tests were conducted on the average pass rates, as shown in Table 4-25, to ascertain statistical significance when using the platform and summarised.

Table 4-25 Summary of All Courses 6 Years t-test pass rates pre- and post-intervention

Two-tailed T-Test results for Pass Rates 2017 - 2022							
	Pre-Intervention		Post-Intervention				
Subject	Mean	Variance	Mean	Variance	t-value	df	p-value
All the courses for 2017–2022.	0,7544651	0,00819152	0,784381455	0,0393894	-0,76848069	51	0,44574573
Financial Management 4	0,79117942	0,00354198	0,763149953	0,04878289	0,594387156	30	0,55670963
Financial Management 3	0,78847103	0,0032802	0,763369727	0,04933113	0,532078641	30	0,5985903
Financial Management 2	0,76806245	0,00647466	0,76913974	0,04871321	-0,02243753	35	0,98222638
Financial Management 1	0,73459354	0,00852307	0,763358812	0,04831773	-0,58826451	36	0,56002751

Ascertaining if there is any decrease in the pass rates during this period after the intervention of the platform is vital.

The data contains t-test statistics for pass rates across various courses and years, comparing pre- and post-intervention results. An analysis of Table 4-25 focuses on each course's mean, variance, t-value, and p-value for pass rates pre-and post-intervention.

For all courses combined over the five years, the mean pass rate increased slightly from 0.7545 (pre-intervention) to 0.7844 (post-intervention). The t-value is -0.7685 with 51 degrees of freedom and a p-value of 0.4458, indicating no statistically significant difference.

Financial Management 1 shows an increase in the mean pass rate from 0.7346 to 0.7634. The t-value is -0.5883 with 36 degrees of freedom and a p-value of 0.5600, indicating no significant difference.

Financial Management 2 exhibits a minor increase in the mean pass rate from 0.7681 to 0.7691. The t-value is -0.0224 with 33 degrees of freedom and a p-value of 0.9822, reflecting no significant change.

Financial Management 3 shows a slight decrease in the mean pass rate from 0.7885 to 0.7634. The t-value is 0.5321 with 30 degrees of freedom and a p-value of 0.5986, indicating no significant difference.

Financial Management 4's mean pass rate decreased from 0.7912 to 0.7631, with a t-value of 0.5944 and a p-value of 0.5567 (df = 30), suggesting no significant change.

Overall, the data suggests that introducing the AI platform did not result in a statistically significant impact on pass rates across the courses evaluated. While there are slight variations in the mean pass rates post-intervention, these differences are not statistically significant, indicating that the AI platform's implementation has not markedly influenced pass rates in the courses analysed.

Students believe that more prolonged engagement with the platform leads to better individual performance. But it remains unclear whether it translates to higher grades. Figure 4-9 Scatter graph depicting Engagement and activity displays activity levels for a specific course, comparing time spent with grade data.

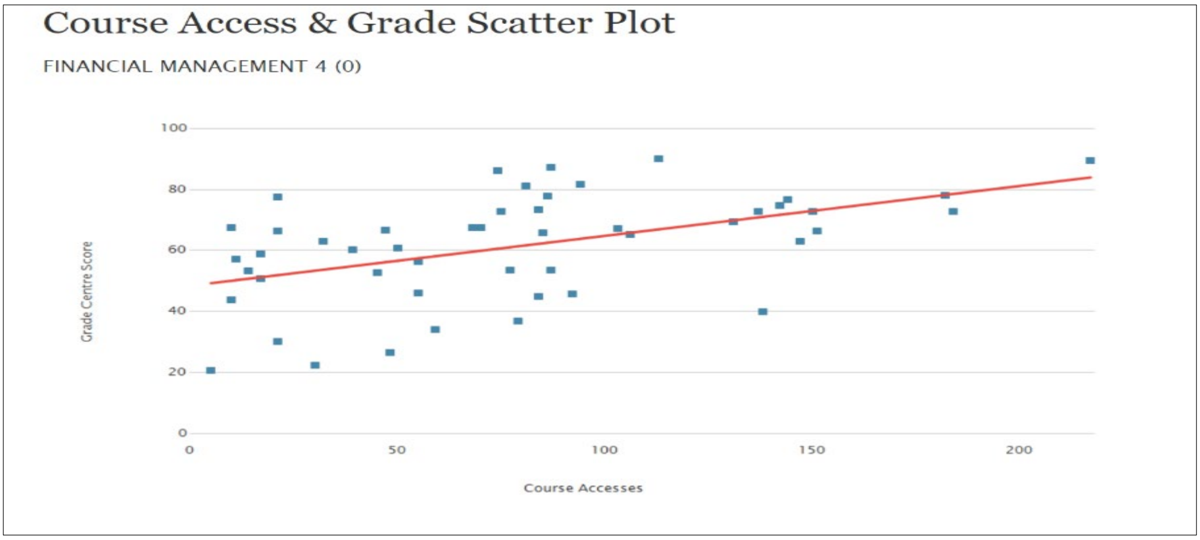

Figure 4-9 Scatter graph depicting Acivity and Grades Scores.

These results show that increased activity leads to more practice and higher grades. Various descriptive statistical test results are displayed and discussed, starting with the correlation mix.

In conclusion, the mean pass rates slightly increase or decrease for each course, and the variance increases post-intervention. However, the t-values and p-values indicate that none of the differences between pre-and post-intervention pass rates are statistically significant. Therefore, the intervention does not appear to have had a statistically significant impact on pass rates in these Financial Management courses during the period analysed. This insignificance means that any observed differences in mean pass rates before and after the intervention are likely due to random variation rather than the intervention itself.

4.6 Results Summation

This chapter offered an empirical study of the effects of an AI peer learning application on students' grade performance and participation levels with the help of a well-developed set of research questions.

The research analysed data in its natural form through a questionnaire containing responses from many individual students, revealing that students appreciated the proposed AI-peer learning platform. The survey results show that the students favour the AI–peer learning platform. Their preference means that while they want to be engaged and have trust in the application affecting their performance, the findings do not provide a direct correlation between engagement and their performance, as determined by the student's grades.

Based on the descriptive statistics, the mean response was notably high, meaning several respondents were inclined to use the platform. The other aspects where the student got lower means are as follows: Generally, the student centricity is positive, as is evident in the above section. The overall pattern is positive, but the mean is lower in some areas. This sample of students appears mildly ambivalent or disinterested. Bartlett's test statistics support that engagement level is significantly related to 'no impact' on performance within the survey categories.

To ascertain the effects of academic proficiency, I relied on t-tests regarding course performance, particularly when comparing results obtained with and without the AI-peer platform. This study helps develop a broad perspective of the outcome angle of an AI-peer learning platform. I do not observe grade differences from the t-tests after the intervention. While cross-sectional data highlighted fluctuations in pass rates and grades as potentially significant, descriptive, inferential tests reveal the need for larger p-values than the conventional alpha level of 0.05 for various courses in financial management. These results suggest that the students are eager to interact with the platform, but the data did not see a marked increase in performance.

These findings raise the question of the difficulties in defining the fit between the epistemological concept of participation as a human activity and measurable performance that adds to the debate concerning the effectiveness of constructivist technology. Therefore, to completely comprehend the influence of AI-peer learning platforms on learning and teaching, future research should examine longitudinal data, qualitative metrics of learner experience, and broader learner outcomes.

CHAPTER 5 DISCUSSION AND CONCLUSION

The last chapter of this research, which includes the Summary, Discussion, and Recommendations sections, has several important roles. The Summary consolidates the statistical analysis results and establishes the relationships and strengths of the variables linked to AI in peer-to-peer learning. The Discussion section reflects on these results and offers implications for educational practices based on the findings of this study. The Recommendations section provides recommendations for future research and policy-making to inform the design and delivery of AI-mediated learning environments.

5.1 Summary

This research addresses a significant gap in knowledge concerning the potential of AI platforms to facilitate peer-to-peer support and influence student engagement, grades, and pass rates in mass learning environments, as shown in Figure 2-5 Conceptual Framework. The problem stems from a lack of understanding of how AI influences student participation and academic achievement, affecting retention as per Tinto's (1975) & Bean's (1980) Retention and Attrition Theories highlighted in Figure 2-6 Concept of Retention-Adapted (Tinto, 1975) and Figure 2-7 Concept of Student Attrition (Bean, 1980), the concepts of Retention and Attrition, respectively. They prompt questions about how the institutions and stakeholders could refine specific aspects of AI to support better academic performance. The study evaluates AI's influence as a machine peer-to-peer learning support tool.

5.1.1 The Rationale

The research questions in Table 5-1 establish the justification for this study. This study has yielded findings that contribute to our understanding of the role of AI in peer-to-peer learning, engagement, belief, and performance, potentially affecting retention. The broader effect of AI assistance, such as peer-to-peer support, on engagement, grades, pass rates, academic achievement, and the student wanting to return underpins the research question and objectives. Table 5-1 revisits the Research Questions with the findings.

Table 5-1 Research Questions and Findings

MQ: To what extent does Peer-to-Peer AI support influence student engagement, grades, and pass rates?	
Sub-questions	**Findings**
RQ1: How do students perceive the influence of AI-facilitated peer-to-peer support on engagement as part of their belief system?	AI-facilitated peer-to-peer support created individualised, flexible, and dynamic learning environments that enhanced student engagement and accomplishment through personalised, adaptive, and interactive learning experiences.
RQ2: To what extent does AI-facilitated peer-to-peer support enhance student grades by assisting students in their return?	Students viewed AI-facilitated peer-to-peer support favourably, noting a 3-5% grade improvement. However, students believed their grades would improve using AI peer-to-peer support tools.
RQ3: To what extent does AI-facilitated peer-to-peer support influence pass rates?	AI-facilitated peer-to-peer support did not statistically change pass rates. However, grades improved between 3-5%.

There are still many gaps in understanding how AI platforms can help in peer-to-peer support and student success in a mass university context. Discussing integrating AI peer-to-peer support with engagement and performance using grades and pass rates helps address this problem and answer the research questions. The motivation behind this research stems from the following key considerations:

5.1.1.1 Knowledge Gaps

The literature reveals a lack of research on how AI platforms can enhance peer-to-peer support and affect student participation, performance, and success rates (Kelly et al., 2023). Research gaps in understanding how AI influences student engagement and academic performance can be identified, particularly in the medical industry, as indicated by Rowe et al. (2022). This research seeks to address this gap by assessing the effectiveness of AI as a peer-to-peer learning support tool.

5.1.1.2 Enhancing Student Engagement

Adaptive learning is considered valuable by educators, although the research evidence is still emerging, given the relatively recent introduction of this approach in higher education (Liu et al., 2017). One of the biggest challenges in online learning environments is student disengagement (Hew & Huang, 2023). This study offers practical recommendations for increasing student engagement in the digital learning environment by investigating how AI can support active learning and self-regulation and decrease student isolation.

5.1.1.3 Aligning with Theoretical Frameworks

Tinto's (1975) & Bean's (1980) Retention and Attrition theories stress the role of student involvement in retention and underpin the study. The research contributes to the existing theoretical frameworks and the literature on student retention and success.

5.1.1.4 Modernising Educational Practices

Given the present trends in the higher education environment and the integration of digital media, research-based findings should guide the design and application of helpful learning technologies (Arco-Tirado et al., 2020). This research provides information that can be useful for educational practices, particularly concerning how AI can enhance P2P learning and academic achievement.

5.1.1.5 Responding to Student Needs

The work also concerns the empirical aspect of determining the students' perceptions and interests in AI-supported peer tutoring (Saat et al., 2004; Tinto, 2017; Trivedi, 2022). To this end, the present study examines students' perceptions of the tools and their impact on engagement and performance to guarantee compatibility between technologies and students in learning (Serrano et al., 2019; Hew & Huang, 2023).

Therefore, this study aims to address the research gap of AI in peer-to-peer learning, improve student engagement, reinforce the retention theories, provide guidelines for educational practices and meet the needs of the learners. This comprehensive approach ensures that the research contributes to academic knowledge and has practical implications for improving educational outcomes through integrating AI technologies.

5.1.2 AI-Facilitated Peer-to-Peer Support

Chapter Four contains the results that allow an analysis of the perceptions of students toward AI-supported peer assisting and its effects on their engagement, grade, and pass rate.

Most students agree that they find AI to be peer-to-peer support. This support for AI illustrates that students know the perceived value of using AI to support peer-to-peer interaction for learning. Student group interactions, immediate feedback, progress, at-risk, performance, and perceived AI usability highlighted AI-assisted peer-to-peer support learning platforms and their influence on peer-to-peer support.

The overwhelming student belief in AI as a peer-to-peer tool is significant. Feedback on the effectiveness of peer-to-peer support provided by AI-assisted platforms was overwhelmingly encouraging, with students acknowledging the importance of peer interaction in their learning and teaching experience in the following areas:

5.1.2.1 Cognitive and Learning Sciences

AI peer-to-peer contributed to cognitive and learning sciences by providing access to new knowledge and various forms of support for collaboration in knowledge-related activities among individuals (Taylor et al., 2021). It promoted proper inter-student relations with tendencies of acquiring similar knowledge, boosting memory and knowledge acquisition. AI, as peer-to-peer, also provides personalised approaches and self-adjusted feedback to students with different learning styles so they can do their work with the assistance of several other students in their own time and at any location (Nel et al., 2023).

5.1.2.2 Explainable AI in Learning and Teaching

To increase student confidence in the institution's strategic peer learning recommendations, XAI evidenced AI and made it more transparent. It helps the facilitators analyse students' interactions and challenges and provide appropriate support and an enhanced learning environment.

5.1.2.3 Human-Computer Interaction (HCI)

The design of the AI platform within human-computer interaction (HCI) significantly influences the effectiveness of AI peer-to-peer support, as highlighted in Figure 2-23. Decisions like the easily recognisable style and design, straightforward structure, and valuable interactions make engaging learning spaces. Discussing, feedback, and cooperative elements such as conferences, immediate feedback, or collaborative tools enrich peer learning communication, as shown in Figure 2-8, The Feedback Cycle (Flodén, 2016).

5.1.2.4 Human-Centred AI

Human-centred AI focuses on creating individualised and supportive learning spaces that address students' emotional and motivational needs (Kem, 2022). It strengthens family-like or peer participation and engagement, personalising motivation and feedback, engagement and psychological well-being, and academic performance illustrated in Figure 2-14 Adapted dimensions of the Flipped Classroom module (Sointu et al., 2023)

5.1.2.5 Learning Analytics

Learning analytics focuses on three areas: analysing the student's interactions with the AI platforms to advance peer-support structures and enhance learning outcomes. Thus, assessing participation rates, contributions, and feedback loops, which consider how students and lecturers engage with the LMS and the platform, allows the lecturer to identify areas for improvement. Applying upgrade modifications and advances in any data strategy to AI frameworks improves performance and student retention.

This research study established the relationship between AI, belief system competence and persistence, academic performance, and peer-to-peer support in a learning context. It examined the effects of the impact practices discussed in Chapter Two on students, including their engagement and beliefs[16].

5.1.3 Engagement

The survey's thematic data indicated students' favourable perception of the AI-peer learning platform to increase student engagement. 84.98% of the students believe that AI peer-to-peer support influences their engagement with the course. This nuanced outcome suggested that while students believe in the platform and are willing to engage with it, they think it should improve their performance. It indicates that while the platform effectively engaged students,

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16 Impact Practices

Impact Practices
Students are working in groups on tutorials.
Group engagement is separate from formal sessions, specifically on assignments.
Opportunities exist for AI in peer tutoring.
The discussion of concepts from added readings with instructors.

additional pedagogical strategies might be needed to translate this engagement into academic gains. It also suggested that other factors may influence grades and performance (Jama et al., 2009). For instance, integrating more adaptive learning algorithms that tailor content to individual learning styles or providing more actionable feedback might enhance the platform's effectiveness in improving academic performance. The findings suggest that the higher the grades of the performing students, the more they will engage with the platform. The following factors further influence engagement with the course:

5.1.3.1 Artificial Intelligence

The study examined how students' beliefs about AI technologies affected their involvement with the course. Although students see AI interaction favourably, how this has affected academic performance specifically, a measure of learning efficacy, Bean & Metzner (1985) is unclear. The platform's ability to enhance thematic involvement does not automatically result in improved academic grade performance. These data imply that although students are able and eager to engage with technology, participation alone will not boost academic performance. The degree of content interaction, the applicability of the materials offered, and the incorporation of AI-driven insights into the teaching and learning process are some factors that may affect how well this kind of engagement leads to quantifiable increases in academic grade performance.

5.1.3.2 AI Engagement in Learning and Teaching

The study concentrated on aspects of platforms with AI support that could affect user engagement. I emphasise two needed components: customised feedback systems and adaptable learning materials catering to every student's requirements and skills. Constructive academic outcomes were associated with features of the platforms, especially those that provided analytics and progress tracking, as illustrated in Figure 3-18, the Performance Report, and Figure 3-20, the Lessons associated with the objectives. This interaction suggests that these insights encourage more effective study approaches. Additionally, the task-assignment mechanisms on these platforms demonstrated enough adaptability to consider varying learning styles and skill levels, suggesting possible widespread adoption across diverse student populations, as seen in Figure 3-22 Creating an Adaptive Course.

5.1.3.3 Cognitive and Learning Sciences

AI as peer assistance substantially impacts the cognitive and learning sciences since it helps students understand and remember the material more deeply (Beck et al., 2023). AI systems offer personalised education by tailoring the curriculum to each learner's cognitive type and rate of learning. This approach maximises learning efficiency and retention by increasing internal and external cognitive load. AI-driven peer-to-peer support promotes self-regulated learning by enabling students to monitor their understanding and adjust their learning tactics.

5.1.3.4 Explainable AI in Learning and Teaching

Explainable AI (XAI) enhances transparency and confidence in AI systems for peer learning by providing brief explanations for recommendations and feedback (Mandouit & Hattie, 2023). This feedback helps students understand the logic behind AI concepts, encouraging deeper involvement. Transparent processes also encourage students to trust AI aid. XAI also assists educators by providing insights into students' difficulties and learning styles, enabling more targeted interventions.

5.1.3.5 Human-Computer Interaction (HCI)

Since AI platform design and usability directly impact student engagement, they are vital to HCI (Ott, 2023). Sound HCI design assures the development of apprentice AI systems that are understandable, interactive, and easily navigable. Attractive aspects such as real-time, data-driven dashboards, friendly competition, and instant feedback accelerate learning, as illustrated in Figure 3-16 Announcements. It reflects a friendly-competition aspect by enhancing the social features of interacting AI systems in peer-to-peer communication and solving peer group problems through collaborative learning.

5.1.3.6 Human-Centred AI

A user-centred artificial intelligence system is an artificial intelligence system that prioritises the users' needs based on the user's perspective (Nagy & Molontay, 2023). Nonetheless, when applied to student-centred learning, the paradigms enhance immersion and the mental aspect of learning while reducing anxiety in students by creating favourable learning environments.

5.1.3.7 Learning Analytics

Learning analytics entails analysing student patterns to determine their interaction with allocated artificial intelligence technologies, as illustrated in Figure 3-26 Item Analysis and Figure 3-27 Category Analysis. It enables professors to use strategies for identifying at-risk students and preventing them from becoming dangerous, as most packages allow instructors to identify a particular student's behaviour and learning style to implement early intervention mechanisms. This form of learning enhances the learning process, aiding in the achievement of an improved response from the AI systems to the ever-evolving needs of the students. Learning analytics enhances the effectiveness of AI systems in improving learning objectives.

5.1.4 Grades and Pass Rates

On average, using AI-enhanced peer-to-peer supports the students' performance by 3-5%. Although this may not be very high, it has significance.

The survey data discussed in Chapter Three under the engagement theme does not show the influence towards positive performance through the t-test score. However, 84.98% of the students thought using the AI platform would increase their grades. There were no direct questions to the students as to whether they believed their grades would be better with the help of the proposed features—the questions related to performance.

Regarding performance and the possibility of returning, the t-test analysis has revealed no marked differences in the means of various groups, particularly in pass rate and average mark. The mean pass rates slightly increased post-intervention. However, the t-statistic is also negative, indicating the post-intervention mean is not significantly higher at a conventional significance level. Are there other external and internal non-academic factors that influence performance and, therefore, grades that the platform did not overcome? The students suggested that the platform should improve performance. However, the data did not support this belief. To further explain the intricacies of these group distinctions, post hoc tests, such as Tukey's Honestly Significant Difference (HSD) or Bonferroni correction, can be employed for in-depth pairwise comparisons among groups.

Interestingly, the students believe that increased engagement improves their grade performance. This belief has a significant emotional context and should impact their vested interest in the courses. It is imperative, however, to exercise caution when inferring causality from this relationship, as other unaccounted variables may also influence grades. The study has unveiled a negative correlation between levels of belief and the likelihood of engagement with the platform, indicating that individuals with lower belief levels tend to exhibit higher participation rates. This lower belief suggests students feel compelled to use the platform rather than wanting to use it. The findings reveal that the time spent on the platform peaks during assessments. This phenomenon may add value to the system by making a difference in performance by allowing specific time on the system in a focused manner. This timed performance is another opportunity for further research.

Grades and pass rates before and after the introduction of the platform remain statistically similar, indicating that the tool's impact on performance may be neutral. However, there was a 3-5% improvement in grade performance, which varied per course and the student's academic year. The older students tend to have performed better. Other factors, like socio-economic factors, may have negatively impacted grade performance that the platform alone cannot overcome. It may suggest that the performance improvement could be significant without other problems. It is up for discussion that institutions should include other factors that impacted performance as part of their overall strategy.

The analysis of academic performance using the AI platform presents a complex picture. The data does not support the initial expectation that enhanced engagement correlates with better academic grade outcomes. Performance is not limited to grade improvement[17]. Performance should include feedback of structured assessments as it has shown to have high motivational value to enhance learning" (Williams, 2014: 567). The perception that increased engagement with the platform leads to better performance lacks statistically significant grade improvement but finds support in the engagement of students through feedback. The emphasis "to" learn rather than "for" learning focuses on grades as a measure of performance (Lynch & Hennessy, 2017). "To" learn focuses on the intent or purpose of an action, while "for" learning emphasises the function or use related to acquiring knowledge. High grades and student learning are not always synonymous (Gijbels et al., 2005). High grades do not define success. This study

17 "currently in higher education, the assessment of learning predominates over assessment for learning'. This is reflected in the pervasive and privileged position given to summative assessment practices in higher education which focus on feedout to students in the form of grades and decreased emphasis granted to engaging students through feedback" (Williams, 2014: 566).

supports the findings of Gijbels et al. (2005). The performance analysis of AI peer-to-peer support by grade only reveals pivotal student learning insights.

Segmenting the data into pre-intervention and post-intervention groups across various financial management courses enabled a nuanced understanding of the impact of interventions. Each table offers a digest of pass rates and average final marks, serving as a springboard for deeper statistical examination.

T-test results are particularly telling, revealing insignificant statistical variances between group means. There is a statistical difference between the groups regarding grades and pass rates, which is considered negligible. This study did not consider other factors influencing grades, such as academic fraud (Nugroho et al., 2023). Each t-test reaffirms insignificant differences in group means. The differences indicate a consistent pattern where the learning and teaching intervention appears to have altered learner outcomes across multiple studies but not significantly.

A further finding is the reduction of the average pass grades between the groups. The platform's uniform application of consistent standards may contribute to this reduction. Lecturers' academic fraud could significantly affect grades pre-intervention (Archibong, 2012; Saat et al., 2004). These external issues were not part of this study.

This study highlights two issues for further investigation: academic fraud and activity timing. Analysis revealed increased student engagement on the platform during assessment periods. Notably, platform usage spiked in March, June, September, and November, coinciding with summative and formal assessments. This trend raises the question: Does the observed marginal increase in grade averages imply greater platform effectiveness when compared to traditional methods of platform use? For instance, marks achieved in three months of conventional teaching equal those from one month of platform usage. This observation warrants further investigation. The following factors further influence grades and pass rates.

5.1.4.1 Cognitive and Learning Sciences

Computer scientists often incorporate AI with learning, improving cognition and learning science paradigms to enhance grade levels and promote better comprehension (Yang et al., 2013). AI systems help learners achieve better results in the learning process by adapting it to its parameters and following the cognitive load theory to avoid increasing external and intrinsic load (Sweller, 1994). The components that enhance performance in these systems include analysing and storing previous knowledge in students and using metacognitive skills to corroborate understanding and reflect on learning strategies.

5.1.4.2 Explainable AI in Learning and Teaching

Explainable AI (XAI) provides a better understanding of the AI recommendations and comments that help teach and provide assurance that learning is vital. In this case, students are likely to follow AI education since they understand the importance of AI education in improving their academic results (Arnold et al., 2022). Explainable Artificial Intelligence (XAI) makes education more efficient since it enables instructors to fully understand students' learning, enhancing how they approach them and their strategies to handle them (Ali et al., 2023).

5.1.4.3 Human-Computer Interaction (HCI)

The technology and the art of implementing AI applications also significantly determine the quality of academic accomplishment, which is a necessary aspect of HCI (Weitekamp et al., 2020). Applying the HCI models makes it easy to design exciting and easy-to-use AI systems Among other vital practices that, when applied, make it easy to create exciting and easy-to-use AI platforms include: This ease of use can be beneficial to lessen other mental barriers that may hinder their learning and improve the settings' interest to the learners. Features such as gamifications, board-like interfaces that let students interact, and feedback options are ways to enhance learning outcomes (Truong, 2016). Social applications of AI assist in developing interpersonal and group communication and, in the process, facilitate learning, which is likely to improve the performance of all the students within a particular team or group.

5.1.4.4 Human-Centred AI

Human-centric AI aims to design an environment of learning effectiveness that puts the users` utility first to boost achievement (Sun et al., 2017). It gives individualised feedback, with an option to appeal to emotions and motivations while maintaining users' preferences. This technique probates participation, contributes to achievement, reduces anxiety, and promotes enjoyment when learning. If implemented in the current AI systems, matching a person's needs allows learners of all ages to reach their maximum potential regardless of their methods and time.

5.1.4.5 Learning Analytics

Learning analytics is a technique that employs data to improve performance in education by analysing the use made by students of AI systems (Ouyang, Wu, Zheng, et al., 2023). Teaching professionals can use it to identify and immediately address obstacles, enhancing AI systems' ability to adapt to students' evolving needs. It may extend to cover improved marks scored in class and overall academic achievement.

Data use and assessment are relatively easy to comprehend, as illustrated in Figure 3-13 Blended lessons and recordings. This easy comprehension means that the supportive learning and teaching intervention intended to help the students improve their grade performance and retention rate did not work as intended. Similar research needs to answer this question to show how this platform made it possible to develop constructive beliefs regarding engagement and learning rather than destructive ones. At the same time, there was only a marginal rise in grades.

5.2 Discussion

Using AI in an environment dominated by the teaching-learning process improves student interaction by providing peer assistance and customising the learning models depending on student preferences. As referred to in Chapter 2, engagement is multi-faceted, and the findings indicate that AI peer-to-peer support has constructively influenced these facets (Glossary and Great Schools Partnership, 2016). Table 5-2 lists the implications of this study’s research choices.

Table 5-2 Implications of the Research Choices

Research Choice	Advantages	Disadvantages	Implications
Using archival survey data	Utilises data in its natural form	This survey reflects on real-world usage and experiences; however, there might be a lack of up-to-date information, which may reduce the validity and practicality of the conclusions drawn.	It provides insights based on real-world usage and experiences; however, it may lack current data, limiting the relevance and applicability of findings.

Research Choice	Advantages	Disadvantages	Implications
Integration of AI in teaching and learning.	It enhances the engagement of students and the use of the learning models.	Risk of dependency on AI and potential for resistance to change.	Improves student participation and individual learning; additional guidance and professional development may be needed to ensure proper use.
Peer-to-peer support through the use of AI for multi-faceted engagement.	The beneficial impact on cognitive, affective, and psychomotor learning outcomes.	Difficulty in assessing and mitigating all aspects at the same time.	Enhances total student involvement, which may help decrease dropout rates and create a more well-rounded learning environment.
Lecturers delivering engaging content.	Increased challenge and fun learning atmosphere.	It is a process that needs the lecturers' time and innovation.	Develops an exciting and enjoyable classroom environment to ensure that students are fully engaged in the class.
Promoting emotional engagement.	It enhances post-lesson morale and optimism about the learning process.	It may be challenging to gauge the emotional effects of the intervention accurately.	Assists in reducing dropout rates through creating a constructive learning atmosphere and addressing students' emotional needs.
Peer group assignments and social learning activities.	Acquisition of social skills in interactions.	Some of the potential coordination issues and unequal participation.	It helps to develop necessary social skills and group work among the learners, thus improving the learning process.
Cognitive load theory-based individualisation.	It enhances understanding and recall of course material.	It may need extensive AI development and implementation.	Promotes individualised learning, which helps the students learn better and with more interest.

Lecturers enhance intellectual engagement by delivering content that creates a fun learning environment during classes (Dogan, 2015). Promoting attitude enhancements of emotional engagement includes engaging favourable conditions, recognising post-lesson mood, and considering help that improves optimism for learning, potentially lowering dropout rates. It is worth underlining that predictable directions help to keep learners engaged and moderate potential variation to maintain the flow of knowledge. Students' physical participation is an exciting learning approach that incorporates movement into the lesson, which helps cut distractions and improve memory, as well as the advantages afforded by the multimedia facility. Students learn interactive social skills through peer group assignments, competitions, and other required social learning activities. Industry engagement narratives were scripted and connected with performances in each AI group case study. Cultural engagement sees universities accommodating different backgrounds through orientation sessions, translations, and multicultural events, which helps lower marginalisation and enhance students' engagement with course material.

Cognitive load theory-based individualisation helps students comprehend, recall, and remember course content. This way, availing an AI helps create an engaging and stimulating learning environment since the content varies depending on the student’s learning ability, and the feedback given is always timely.

A brief on Explainable Artificial Intelligence (XAI) shows that enhancing student compliance by building trust improves student participation as they believe in instructions. This theory enables facilitators to identify student challenges for extra assistance to improve learning engagement and the classroom atmosphere.

The value of sound algorithmic design cannot be under-stressed for enhancing students’ interest in the fundamental concepts of human-computer interfaces. The levels of interactivity and user-friendliness enhanced by incorporating game-like elements, dashboard interfaces, and other features make meaningful learning more enriching. The social aspect of AI-enabled improved organisational learning and interactions between students and stakeholders, bringing joyful learning. Emotions are enhanced in human-centred AI systems, which encourage learning, alleviate fear, and make learning fun by boosting morale and issuing appropriate encouragement and feedback, increasing students' engagement.

Learning analytics gave information on the behaviours and learning patterns of the students by analysing data on how the students engaged with the AI platform, which helps the traditional peer tutors improve engagement and give interventions at the right time.

The study reviewed several research options, explaining why the researcher did not select a particular option and identifying possible missed ones, as illustrated in Table 5-3. The traditional form of peer-to-peer support is face-to-face, which is limited in terms of feasibility for large class sizes and may lead to enhanced communication and peer-to-peer support.

Table 5-3 Alternative Research Choices and Implications

Alternative Choice	Reason for not Selecting	Potential Benefits Lost
Traditional face-to-face peer-to-peer support	Lack of scalability in large class settings.	Improved ability to communicate and interact with others, including peers, may result in better friendships and sources of support.
Blended Learning without AI	The absence of individualised learning and customisation options	The advantages of using both online and offline teaching methods include increasing students' interest and achieving a good balance of learning.
AI-Facilitated Individual Learning Only	It does not include the advantages of peer-to-peer support and social learning.	Individualised learning may not get the required social skills and peer interaction in the learning process.
Solely Text-Based Online Platforms	Lack of interactivity and engagement options	This aspect helps students who like reading more than interactive content since they can access the information with less cognitive load.
Manual Data Collection and Analysis	Slow and not as effective as the use of automated AI.	In-depth, qualitative insights from manual analysis might offer a better, more nuanced data interpretation, capturing subtleties missed by automated processes.
Instructor-Led Online Learning	Lack of flexibility due to reliance on the instructor's schedule and materials	Direct contact with the instructor can help students get feedback and explanations, making learning more active and influential.
New Survey Instead of Archival Data	The challenge that students who used the platform had left the university	Current insights and feedback from recent users could provide more relevant data, allowing for timely adjustments and improvements based on recent experiences.

Before the integration of AI, blended learning did not offer individualised learning opportunities and the advantages of both online and offline learning. AI-supported self-directed learning does not involve peer interaction and collaboration, which can harm the development of interpersonal skills. Text-based-only platforms did not have the element of interaction that could be ideal for learners more comfortable with reading. Manual data collection was slower and less efficient than automated AI, but it might provide more detailed qualitative data.

Teacher-mediated online learning was not flexible even though it offered important direct lecturer feedback. Finally, using a new survey instead of archival data had difficulties; students who used the platform were no longer in the university and could not provide current information and feedback for changes. Archival data appears naturally, which is an advantage for this study.

5.2.1 AI-facilitated Peer-to-Peer Support

AI integration into peer-to-peer learning experiences enhances interactivity and cooperation in the learning processes. It effectively connects students with the same learning objectives to form healthy interpersonal relationships and problem-solving for the expected performance.

XAI enhances the efficacy of peer help by increasing students' confidence and improving the explainability of outcomes. If students understand why AI is necessary, they are more likely to engage in a function effectively and acquire the skills needed to engage AI in collaborative learning.

By describing or outlining the different interactions of the conceived work, the designed HCI facilitates humane modelling as it evaluates AI systems to enhance cooperation—interest-based interaction tools integrate discussion forums and dashboard options, encouraging students' co-interaction and co-participation. The AI systems consider the human-constructive approach and cultivate peer-to-peer knowledge acquisition by considering students' emotional and motivational engagement demands. The adaptability of the feedback and assistance provided to each student and the emphasis on cooperative work while reducing competitiveness pressure make these systems a favourable learning environment.

Based on this categorisation, learning analytics helps facilitators assess insights from peer-to-peer interactions, identify concerns, and offer specific interventions. Data-driven strategies facilitate the progress of the AI system, benefiting peer learning and enhancing academic performance and student contentment through the utilisation of the AI peer system. Artificial intelligence improves peer-to-peer learning by offering customised, inclusive, and interactive opportunities. Integrating AI into the academic setting leads to higher educational graduate-attributed outcomes, motivation, cooperative learning, and fruitful peer relationships.

5.2.2 Engagement

The study also shows that applying AI in peer learning constructively impacts students' engagement. AI-peer learning provides students with customised, adaptable, and efficient learning spaces that increase student motivation through personalised interactive experiences. This engagement by Tinto (2017) & Bean (1980), Retention Theory and the Theory of Attrition emphasises the role of group interaction.

The students are optimistic about using AI in peer learning, as they can learn at their own pace and in the most suitable manner. Incorporating AI practices makes learners more confident and ensures they incorporate AI feedback into their work, improving academic performance. The optimistic view of AI in learning shows that it can beneficially impact student achievements. AI-enhanced peer learning feasibly makes the student come back to university. These findings underscore the importance of AI in facilitating peer relationships and enhancing academic achievement.

5.2.3 Grades and Pass Rates

AI can improve academic performance by promoting self-regulated learning and enhance academic achievement by allowing students to monitor and modify their learning processes, two crucial metacognitive strategies. Self-control increases intrinsic cognitive load and reduces excessive strain.

Explainable AI (XAI) improves academic performance by providing clear insights into AI-generated feedback, fostering trust among learners, and enabling the successful integration of AI recommendations. It also aids teachers by providing a comprehensive understanding of students' learning challenges. AI platforms should be designed with user-friendly interfaces, gamification, and real-time feedback to enhance academic achievement, foster peer relationships, and promote collective problem-solving in collaborative learning environments.

Human-centred AI systems enhance academic success by considering the motivational and emotional aspects of learning. They provide customised support and adaptive feedback and reduce anxiety, promoting a supportive learning environment that improves students' performance. Learning analytics enhances academic performance by providing data-driven insights into student AI usage. Lecturers can identify at-risk students and offer early interventions, as AI systems are regularly updated to meet student needs. When used as peer-to-peer support, AI offers transparent, personalised, and adaptable learning opportunities, significantly enhancing academic performance. Strategic AI integration in learning environments cultivates greater comprehension, drive, and teamwork, improving academic performance and student achievement.

In conclusion, using AI in peer-to-peer support enhances the learning experience, increases support effectiveness, constructively impacts student success and supports the literature.

5.2.4 Substantive Reflection

The findings of this study are consistent with and build on prior research in several important ways. The enhancement of student engagement and the delivery of personalised learning through AI aligns with the study by Liu et al. (2017) on adaptive learning systems and presents a direction for future research. AI-enabled peer-to-peer support for cognitive, affective, and psychomotor learning outcomes accords with Hew & Huang (2023) & Jia et al. (2023), who underscore the value of active learning and peer collaboration in online teaching and learning.

The importance of meaningful content, as discussed by Dogan (2015), is reflected in your study, emphasising the need for lecturer creativity to capture students' attention. Emotional engagement findings support Tinto's (1975) & Bean's (1980) proposition that help reduce dropout rates and improve students' well-being.

The focus of my study on social learning activities aligns with Vygotsky's (2011) cognitive development through social interaction while using cognitive load theory, which aligns with Sweller's (1994) principles of handling extraneous load to enhance learning. Applying Explainable AI (XAI) in my study is consistent with Adadi & Berrada's (2018) argument on explainability to foster trust, thus underlining its significance in the educational context. As discussed in my study, the archival data provides some natural insights, Eisner (2017) and current data collection. The learning analytics in my research are consistent with Siemes's (2013) work and show how data can improve conventional peer tutoring and educational interventions. In conclusion, my study findings align with previous literature, extending current knowledge in the application of AI in increasing student engagement and achievement.

5.3 Addressing the Research Questions

Table 5-4, through a bibliometric literature review, identified a problem in universities: a lack of knowledge on how AI peer-to-peer support influences students' engagement, grades, and pass rates, which affects retention according to Tinto's (1975) & Bean's (1980) Retention and Attrition Theories.

Table 5-4 Study Relative to Literature

Research Question	Literature	My Study	Related Research	Comparison and Reflection
RQ1: How do students perceive the influence of AI-facilitated peer-to-peer support on engagement as part of their belief system?	AI Integration in Education	This platform has a supportive effect on student engagement and individualised learning.	Liu et al. (2017) suggest adaptive learning systems are promising but require more evidence-based studies.	My findings are consistent with those of Liu *et al.* (2017), who support the idea that AI increases engagement and learning personalisation and thus reinforces the need to explore the use of AI in adaptive learning systems.
	Peer-to-Peer Support via AI	It improved cognitive, affective, and psychomotor learning achievements.	Online flipped classrooms foster active learning and self-regulation by Hew & Huang (2023) & Jia *et al.* (2023).	This study underscores the value of peer-to-peer support and active learning formats, indicating that AI may enable a more inclusive approach to student engagement and mitigate feelings of loneliness.
	Lecturer-Delivered Content	Higher student participation with entertaining and exciting material.	Dogan (2015) posits engaging content improves student engagement and learning outcomes.	My finding is consistent with Dogan's (2015) work, highlighting the importance of exciting and complex material to keep students involved and achieve better results.
	Promoting Emotional Engagement	I am boosting post-lesson morale and optimism about learning.	Tinto (1975) & Bean (1980) advocate emotional engagement is crucial to student	This study is consistent with the theories of Tinto and Bean, which suggest that creating a

Research Question	Literature	My Study	Related Research	Comparison and Reflection
			retention and success.	supportive emotional climate can assist in decreasing dropout and increasing students' satisfaction.
Research Question	**Literature**	**My Study**	**Related Research**	**Comparison and Reflection**
RQ2: To what extent does AI-facilitated peer-to-peer support enhance student grades by assisting students in their return?	Social Learning Activities	I am Promoting social skills through peer-to-peer support activities and group tasks.	According to Vygotsky (2011), interactive communication is a requirement for cognitive growth.	This study aligns with Vygotsky's (2011) theory, which emphasises the role of social interactions in developing cognitive and social skills necessary for effective learning.
	Cognitive Load Theory	It has individualised learning experiences for improved comprehension and retention.	According to Sweller's (1994) cognitive load theory, the load should be reduced as much as possible to avoid unnecessary load.	This study aligns with Sweller's (1994) theory, showing that AI-based individualisation enhances cognitive load management and, thus, learning outcomes.
	Explainable AI (XAI)	Fosters trust and increases student engagement due to increased accountability.	According to Adadi & Berrada (2018), XAI is a technique that focuses on enhancing the explainability of AI for increased trust and reliability.	My findings are congruent with Adadi & Berrada's (2018) principles, indicating that the explanation of AI systems can improve confidence and adherence, thus improving student participation.
	Archival Data Use	I Used natural raw data. Using an alternative instrument was problematic as students had left the university.	Works also show that obtaining natural, current and credible information for proper assessment is crucial (Eisner, 2017).	Archival data helps provide natural insights. The data is analysed in a non-manipulated and natural form. However, there is a need to use up-to-

Research Question	Literature	My Study	Related Research	Comparison and Reflection
				date data to capture the current level of student engagement. This study is consistent with Eisner (2017).
RQ3: To what extent does AI-facilitated peer-to-peer support influence pass rates?	Learning Analytics	It served as an extension of traditional peer tutoring, giving information about student behaviour and learning styles.	Siemens (2013): Learning analytics makes it possible to analyse learning and the contexts in which it happens.	This application of learning analytics is consistent with Siemes's (2013) study, showcasing how the data-driven approach can complement and improve conventional pedagogical approaches and strategies.

This problem extended to the academic problem of poor student performance at universities. Theoretically, the problem lies in the insufficient understanding of the mechanisms by which AI can enhance peer-to-peer learning environments and support retention, thereby contributing to existing educational theories. In response to these problems, this research investigates the use of AI to facilitate peer-to-peer learning, focusing on its effects on participation and performance. Theoretically, this case study has implications for theory development and testing. On the methodological level, it provides a template for further research. And on the practical level, it presents lessons for managers and policymakers. The primary contribution is in artificial intelligence peer-to-peer support, enhancing our understanding of how AI can improve student engagement and academic performance and retain students at university within peer-to-peer learning environments. The role it plays in improving the teaching and learning process, especially in this field, is indispensable. As a result of the timely combination of technology and proposal of areas to advance, the study provides the necessary solutions to raise the level of education.

Additionally, the research has social significance in various AI peer-to-peer support training and education aspects. It shows how the educational process changes and the problems that may occur when traditional methods meet technological advancements. The study also reveals the relationship between theoretical problem-solving and practical application. Most importantly, it ensures that learning and teaching and continuously innovating AI peer-to-peer support are better integrated, thus addressing the gap between the two areas. Through the study, I examined the influence of AI-enabled peer learning on student engagement, grades, pass rates, and performance, focusing on crucial questions related to its effects. The distinctions created affect the students’ willingness to return to university. The AI platform as peer assistance in instructional environments affected students' performance and engagement because it offers individualised, flexible, and engaging learning opportunities. It did not statistically change, negatively or positively grade results. There was an improvement in grade performance. It did improve engagement through real-time feedback, personalised content delivery, and intuitive interfaces, arguably improving achievement.

Table 5-5 Research Questions, Objectives and Findings

MQ: To what extent does Peer-to-Peer AI support influence student engagement, grades, and pass rates?		
Sub-questions	**Objective**	**Findings**
RQ1: How do students perceive the influence of AI-facilitated peer-to-peer support on engagement as part of their belief system?	To understand how such systems influence their engagement and overall learning experience, one should study Tinto’s (1975) Retention Theory and the Theory of Attrition (Bean, 1980).	AI-peer learning created individualised, flexible, and dynamic learning environments that enhanced student engagement and accomplishment through personalised, adaptive, and interactive learning experiences.
RQ2: To what extent does AI-facilitated peer-to-peer support enhance student grades by assisting students in their return?	To what extent does AI peer-to-peer support influence grades as a component of the Tinto (1975) Retention Theory and the Theory of Attrition (Bean, 1980)?	Students viewed AI-assisted peer learning favourably, noting slightly higher grades of 3-5% due to customised and adaptable learning options.
RQ3: To what extent does AI-facilitated peer-to-peer support influence pass rates?	To what extent does AI peer-to-peer support influence pass rates, a component of the Tinto (1975) Retention Theory and the Theory of Attrition (Bean, 1980)?	AI-enabled peer learning did not statistically change pass rates. The assumption is that performance improved due to lowering cognitive load, boosting efficient learning, and matching content to individual cognitive styles. Specific features like real-time feedback and adaptive pathways are imperative.

These characteristics support a more profound understanding and ability to maximise learning efficiency per the cognitive load theory. Additionally, the AI system supports metacognitive techniques, which let students track their development and modify their study methods for better academic results. These contributions are a direct response to the research questions of this study. Table 5-5 summarises the primary research questions, objectives and findings.

RQ1: How do students perceive the influence of AI-facilitated peer-to-peer support on engagement as part of their belief system?

The AI platform as peer assistance in instructional environments affected students' engagement constructively because it offers individualised, flexible, and engaging learning opportunities. It did not statistically change, negatively or positively grade results. It did improve engagement through real-time feedback, personalised content delivery, and intuitive interfaces, arguably improving achievement. These characteristics support a more profound understanding and ability to maximise learning efficiency per the cognitive load theory.

In conclusion, student engagement with the AI platform does not statistically influence grades or pass rates significantly. Additionally, the AI system supports metacognitive techniques, which let students track their development and modify their study methods for better academic results.

RQ2: To what extent does AI-facilitated peer-to-peer support enhance student grades by assisting students in their return?

Students perceived the AI-facilitated peer-to-peer support favourably, noting that the AI platform. The students believed that they would see an increase in their grades. Grades improved by 3-5%.

RQ3: To what extent does AI-facilitated peer-to-peer support influence pass rates?

AI-facilitated peer learning did enhance student success, not necessarily student grades, by combining learning materials with each student's unique cognitive style and speed. This tailored approach promoted effective learning and, by assumption and retention, lowered unnecessary cognitive load and raised intrinsic cognitive load. Explainable AI (XAI) provided transparent feedback, enabling students to successfully integrate AI coaching into their learning processes. Human-centred AI systems improved performance by reducing fear, creating a favourable learning environment, and offering personalised and adaptive support.

Some features of the AI systems, such as adaptable learning pathways, real-time feedback, and user-friendly interfaces, impacted academic performance. These qualities facilitated the development of individualised learning plans that catered to each student's requirement and learning style, resulting in increased understanding and enhanced academic achievement. Learning analytics enhanced academic performance through targeted interventions that provide meaningful student interactions and performance data.

MQ: To what extent does Peer-to-Peer AI support influence student engagement, grades, and pass rates?

The study's primary research question aims to determine the effectiveness of AI peer-to-peer support on student engagement, achievement, and pass rates based on the outcomes of the three sub-questions.

RQ1 focused on students' perceptions of AI-supported peer-to-peer support on engagement, and the results demonstrated that the AI platform enhanced engagement through individualised, flexible, and interactive learning. While this did not significantly improve the grades, it increased engagement by providing feedback, delivering content based on the learner's preferences, and using interfaces that are easy to navigate, which aligns with cognitive load theory.

RQ2 focused on the influence of AI peer-to-peer support through the AI-mediated platform on students' grades. The 3-5% increase in student's grades may be attributable to the influence of AI peer-to-peer support, albeit statistically insignificant.

RQ3 was concerned with the effect of AI peer-to-peer support and whether, with the help of AI, it affected pass rates. The AI peer-to-peer support system improved student grades (3-5%) but did not improve pass rates. It may have impacted the students' decision to return to university. This aspect of deciding to return may be a case for future research. It addressed different cognitive modes and rates, thus enabling effective learning and memorisation. Due to the use of Explainable AI, students can get precise feedback, and therefore, institutions should consider incorporating AI peer-to-peer support into their learning processes. Human-centred AI systems addressed fear, fostered supportive learning environments, and provided individualised, dynamic assistance.

In conclusion, the use of AI in peer-to-peer learning improves student participation. It positively impacts their grades and pass rates, between 3-5%, mainly because of the personalised and adaptive learning and supportive learning environment—research questions 1-3 address the main research question. The final sections of the study display a matrix and an adapted conceptual framework of the overall findings, recommendations, limitations and delimitations.

5.4 Conceptual Framework

This section returns to the matrix where the platform occupies the personal engagement-performance (EdP) cell by highly categorising AI peer-to-peer support within engagement and persistency, as illustrated in Figure 5-1.

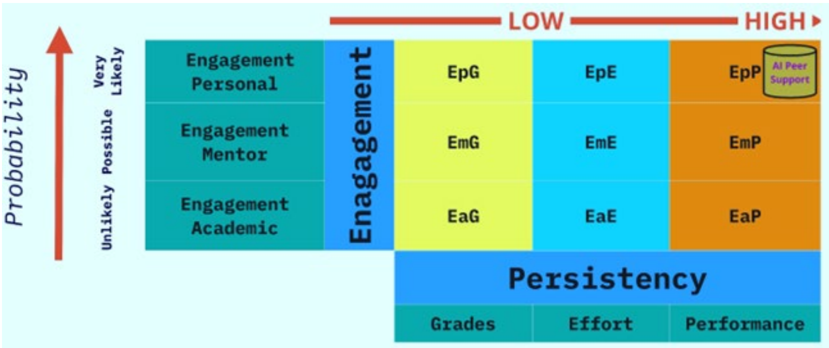

Figure 5-1 The adapted matrix categorising Engagement and Persistence.

Based on the findings and the conclusions, the matrix reveals:

Low Probability (EpG, EmG, EaG): This reveals that AI peer-to-peer support can enhance participation in personal, support and academic intercessions, but these cannot alter grades holistically. Many factors define the grades – the lecturers' quality, how hard the students study, and other considerations. Suppose one focuses on using AI to enhance the quality of the interaction with peers or academics without considering other causative factors. In that case, the chances of receiving increased grades are low.

Moderate Probability (EpE, EmE, EaE): AI peer-to-peer support is not highly beneficial for students but is not detrimental to their endeavours. AI can spur students into working harder in the personal, peer-to-peer support, and academic domains. This effort is reasonable compared to the tendency to concentrate on increasing grades, a factor that is relatively easier to address. It reveals how much students can do depending on the help they receive from teachers or parents.

High Probability (EpP, EmP, EaP): When constructing self-organising complex systems, the relationships between AI peers effectively improve overall performance. It will help to increase respective involvement in the personal, tutor and academic aspects. AI should contribute to enhancing the learning persistency process and performance. Performance, however, is broader than mere scores, including the attainment of knowledge, skills, and interest and its application, enhanced by participation.

This matrix summary is reasonable because it relates AI peer-to-peer support to the extent to which students directly engage in grades, effort, and performance. This support is justified based on the notion that different areas of student learning involve ability, effort, and prior knowledge. Perhaps the level of personal involvement is the most significant aspect of AI peer-to-peer support in increasing effective multilateral personal, mentor, and academic performance. This significance means there is a need to embrace AI approaches focusing on student participation and academic achievement.

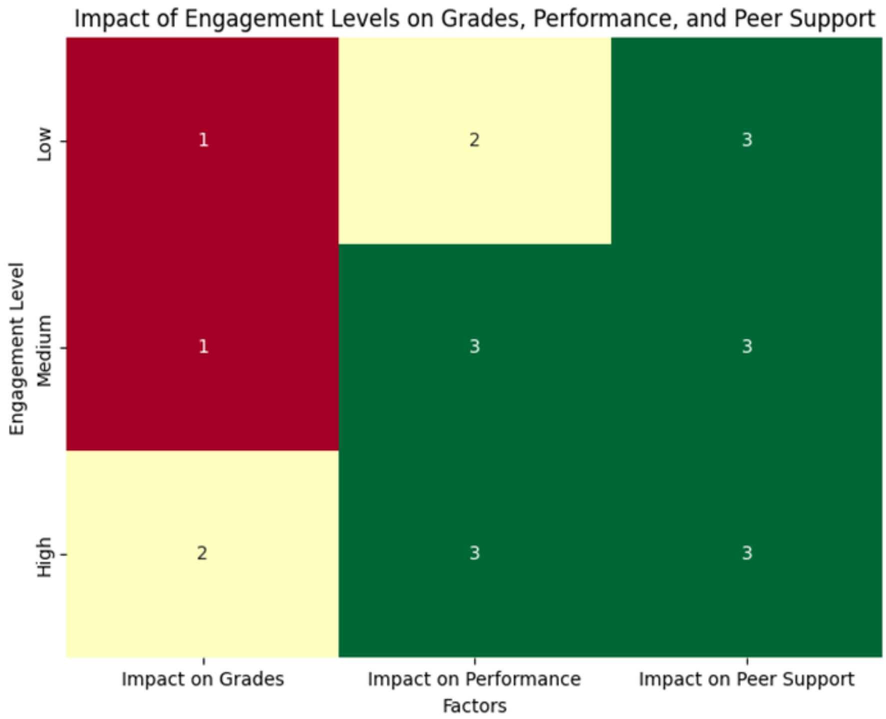

Figure 5-2 Effectiveness of Engagement on Peer-to-Peer Support, Grades and Performance

Figure 5-2 illustrates how increased engagement correlates with performance and peer-to-peer support differently. The matrix reveals that increased engagement levels do not significantly boost grades but impact performance and peer-to-peer support. High engagement consistently leads to improved performance and peer-to-peer solid support. This improvement suggests that nurturing engagement in AI-learning environments can significantly enhance collaborative and performance outcomes, even if it does not directly translate to higher grades.

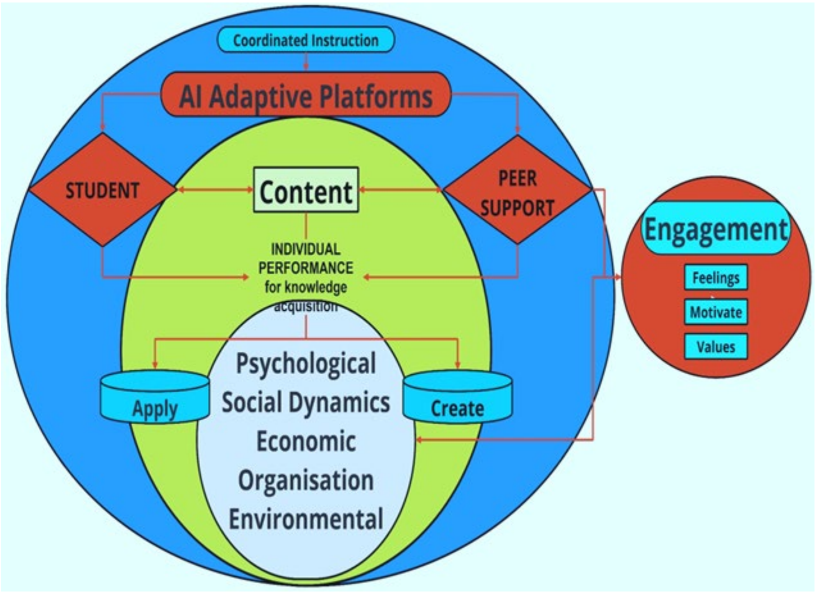

Figure 5-3 Post-Finding Conceptual Framework

The study concludes a statistically significant relationship between learners' beliefs and their inclination towards engagement with the AI-peer platform, thereby adapting the conceptual frameworks. Following on from the matrix is the post-findings conceptual framework, Figure 5-3, which shows a slight restructuring separating engagement from performance.

5.4.1 Engagement and Performance Separation

Initially, I viewed engagement as a single ingredient that drives individual performance. The changes in the new framework make engagement an outcome similar to performance, indicating that engagement cannot cause a change in grade performance and vice versa. This cause means a shift from prior understanding where increased student engagement translated to better grade performance. Even though engagement benefits learning, it does not always enhance grade performance. It is possible to identify distant variables that influence learner performance outcomes by understanding the results that lead to student success.

These areas demonstrate that the idea of an AI adaptive platform and data analytics as a significant element can be instrumental in improving the student's performance according to the individual student's needs. This improvement indicates that there is a need for the integration of more technology to enhance the learning environment. It depicts the relationship between content and student performance. Academic learning outcomes for curriculum and instruction creation require timely and higher-quality content.

5.4.2 AI Peer-to-Peer Support

Based on the extended learning journey concept map I have constructed, student support and content are mutually exclusive and complementary services that engage with student support peers are imperative. The AI adaptive platform aims to improve student interaction with the university system. This type of interaction enhances relations and student involvement. Improved involvement benefits individual student learning, especially in acquiring new knowledge.

Within systematic learner behaviours and communication activities, AI peer-to-peer support enhances the learning environment's psychological, social, economic, and organisational limitations. Therefore, AI-peer-to-peer support enhances learners' activities in transforming knowledge and encourages the development of organisational commitment based on the three-factor framework of effect, valence, and values.

5.4.3 Student Positioning

It is also pivotal to locate a definite place for the student, somewhere in the middle to the left in the given framework. For one part of the content, the student interacts with the platforms and forms of help, focusing on AI compatibility. This positioning shows the student not only as the subject that constantly receives knowledge but as an active subject, eliminating such ideas as accepting the knowledge and discussing coordinated actions. Emotions, motivation, and values influence knowledge acquisition among the students and the learning process. Psychological, social, economic, organisational, and environmental perspectives help understand knowledge acquisition in this performance.

5.4.4 Constructs

The changes implemented in the new framework are confined to engagement regulating experiences and exclude grade and pass rate performance. Engagement-influencing constructs include self-efficacy, motivation, and interest. This view distinguishes between performance and engagement regarding the constructs' effects, with the AI platform immediately influencing engagement and leading to desirable outcomes. Figure 5-4 transposes the concept into a mindmap.

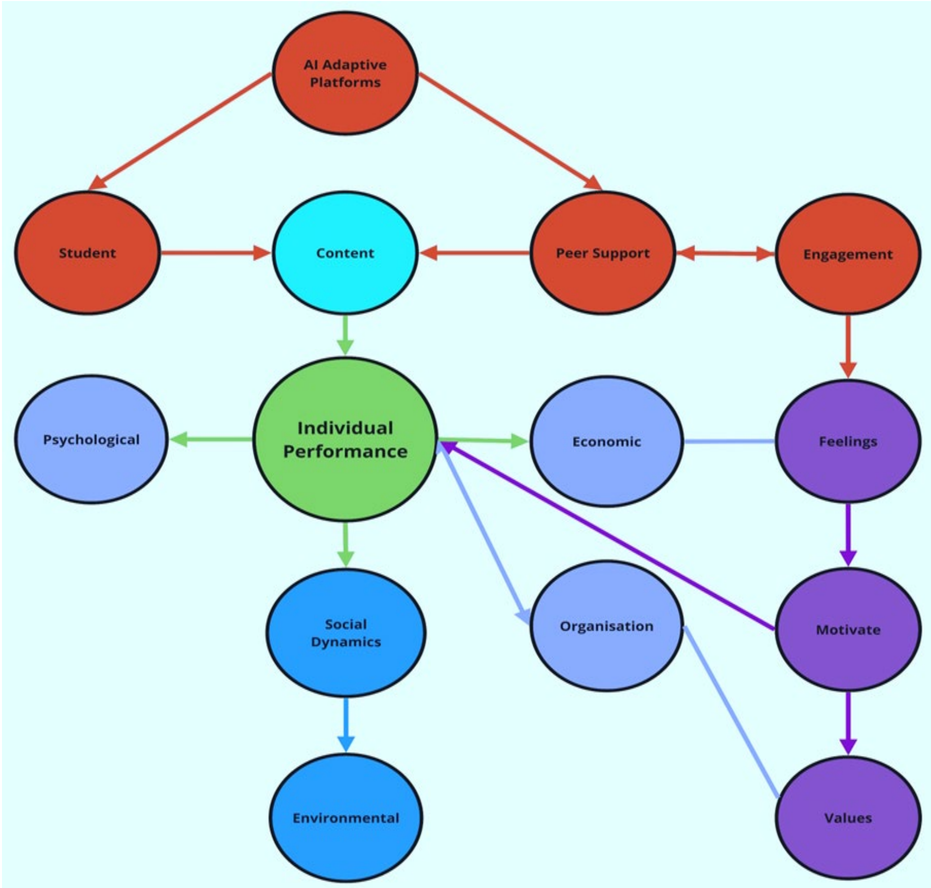

Figure 5-4 Conceptual Mind Map for AI in Peer-to-Peer Learning

Figure 5-4's conceptual mind map illustrates the relationships between the many components involved in acquiring knowledge. Below is a summary of the elements and how they relate to one another:

5.4.5 AI Adaptive Platforms

The top node represents technology-driven systems that customise learning opportunities for each student. This node connects to Student and Peer-to-Peer Support, indicating that AI platforms facilitate direct student engagement and peer-assisted learning.

5.4.6 Student

Positioned on the left, representing the learner. Connected to Content, showing that students engage directly with learning materials.

5.4.7 Peer-to-Peer Support

Peer-to-peer support on the right represents the collaborative aspect of learning. It is connected to Content, indicating that peer interactions enhance the learning materials.

5.4.8 Content

Central to the framework, representing the educational materials and resources. Linked to Individual Performance, indicating that engagement with content impacts performance.

5.4.9 Individual Performance

The individual performance node is positioned below the Content, representing the outcome of the learning process. Multiple factors influence this node: psychological, social dynamics, economic, organisational, and environmental.

5.4.10 Engagement

The node on the far right represents the emotional and motivational aspects of learning. It connects to Feelings, Motivation, and Values, indicating that engagement involves emotional responses, motivation, and personal values. These aspects further influence Individual Performance. Psychological, social dynamics, economic, organisational, and environmental factors are positioned around Individual performance, showing that various dimensions impact learning outcomes. Each factor represents a different aspect of the learning environment and personal circumstances. This mind map does not represent scales or sizes. Instead, it focuses on the relational dynamics and how different elements interact to influence knowledge acquisition. The conceptual framework illustrates that knowledge acquisition is a multi-faceted process influenced by technology (AI Adaptive Platforms), social interactions (Peer-to-peer support), and various individual and contextual factors (Psychological, Social Dynamics, Economic, Organisation, and Environmental). Engagement, including feelings, motivation, and values, is crucial in mediating these influences on individual performance.

Contrary to popular belief, integrating adaptive systems into educational institutions does not mean replacing human teachers with computers. Instead, human planners, monitors, interveners, and interactors must actively participate to achieve effective adaptive learning. Research on the financial ramifications is warranted, but early cost indicators suggest the platform is less costly than the recommended literature. In adaptive learning, the instructor's involvement remains crucial. This research determined how integrating AI in the form of peer-to-peer support in universities influences students' participation, grade performance, and pass rates and consequentially affects student continuation. From the study findings, I present the recommendations and limitations.

5.5 Recommendations

All students should be allowed to follow specific paths and ongoing AI feedback to optimise student achievement and build compelling attendance. Include predictive artificial intelligence as part of student support. Integrating predictive analytics within AI systems can detect students who might face difficulties in their learning progress, offering extra support to those on the verge of failure and increasing their chances of success. Early identification and prevention strategies for at-risk individuals can enhance educational success by identifying and assisting students prone to aggressive acts. However, all students should have access to AI peer-to-peer support, not limited to those at risk. This inclusion is a proposed policy recommendation.

Interaction with the developers of AI is congruent in developing appropriate platforms that will enhance the delivery of educational objectives supported by AI systems.

Policy inclusion stipulating and encouraging the use of AI for co-curricular-induced learning activities can help boost peer-to-peer support and participation levels. University learning and teaching policies must consider the kinds of AI learning applications to ensure platforms adapt to various forms of knowledge, benefiting learners engaged in different types of learning.

Lastly, addressing ethical concerns in using and adopting AI-integrated learning systems prevents unfair usage. Integrating ethical aspects into the AI peer-to-peer support policy is integral to the AI peer-to-peer support implementation decision.

5.6 Limitations

The study's outcomes are specifically contextualised and thus do not necessarily generalise to other learning/teaching environments. The study has some limitations regarding variables because it failed to consider factors that might impact performance and poor retention rates. The study focused on one independent variable, Connect®, limiting the scope of the findings since it did not evaluate other platforms as tools to achieve the study objectives. Note that different AI platforms are inaccessible or not implemented at other institutions. Some variables might have been collected or analysed with bias or subjectivity, such as the archival survey data instrument not explicitly created for this study. Thus, subjectivity and prejudice could have affected the results. Grades as a variable have disadvantages, such as the possibility of dishonest practices and the fact that they depend on the time spent.

Another limiting issue is platform control and authorisation, which requires institutions to engage with creators to customise the algorithms to meet the institution's specific curriculum requirements. Currently, developers create the platforms generically. All stakeholders should consider a future policy for AI-integrated university-specific learning environments. The study had some limitations regarding contextual factors since it was mesoscopic and did not consider factors such as the level of difficulty of the course and the quality of the instruction. The study may have only considered certain variables while ignoring other factors that could have influenced the study's outcome. These limitations highlight the importance of future research on AI-facilitated peer-to-peer support in mass educational settings.

5.7 Delimitations

The delimitations indicate what the research did and did not cover, defining the parameters and extent of this investigation. I purposely set these parameters to make the study more doable and pertinent to the research issues while focusing on the problem. The study used one AI platform, which may not fully represent alternative platforms in terms of taxonomy and features. The consequence is a possible misalignment between university and student outcomes. The study focused on AI's impact on student performance and peer-to-peer learning, highlighting its limitations and potential educational applications without addressing its broader implications. Conducting the research within a specific academic setting limits its generalisability to other educational environments, geographical locations, or grade levels.

The study concentrated on an AI peer-to-peer support platform, performance, and engagement as vital factors but overlooked other influential factors such as socioeconomic status, prior education, or external support systems. The study also refers to retention, which is not related to the ability to retain knowledge but rather the desire of students to return to the university. The method used in this study was a mixed-methods approach to gain a better understanding of the research problem. Though it helped to address the study's focus, applicability, and objectivity, this approach also restricted the possibilities, potential results, and impact of other strategies.

5.8 Future Research

This study on AI-based peer-to-peer support has served as a starting point for further exploration of how AI can help increase student success, performance, overall performance score, and engagement. They outline how practitioners can expand and assess supportive approaches to AI for learning in future research. One suggestion is to conduct other cross-cultural studies to evaluate AI within different learning environments and explore the cultural effects on learning with the help of AI in pair and pair and more group settings. Expanding research to include diverse educational settings, such as different academic levels and geographical locations, may increase the generalisability and applicability of AI tools. Additionally, future studies should include more variables to provide a comprehensive perspective and analyse other factors, such as socio-economic status, past learning background, and encouragement systems.

As evidenced by this thesis, peer learning enhanced with AI has beneficial impacts on achievement and student engagement. Therefore, the changes enabled by AI platforms in meaning-making are advantageous and have improved learning. However, there is limited insight into how these alterations affect academic performance improvements in different settings, particularly affecting diversity. Future research on artificial intelligence and its long-term effects should focus on cross-cultural and long-term studies in diverse educational contexts. Establishing a continuous linear improvement of AI could increase the effectiveness of AI systems and provide equal learning opportunities. Data analytics and ethical considerations drive these developments. The future of learning and teaching will depend on how well educational institutions comprehend the complex consequences of artificial intelligence.

5.9 Final Contributions

The theoretical, methodological, and practical contributions detailed here explain the primary factor in reducing bias in this study and similar future research. Consequently, this section attempts to compile theoretical insights, methodological advancements, and practical implications of the research to demonstrate its extensive influence on AI-facilitated peer-to-peer learning.

5.9.1 Original Contribution

This research uniquely contributes to AI in education by presenting a novel integration of AI-facilitated peer-to-peer learning within the frameworks of Tinto's Retention Theory, Bean's Theory of Attrition and Kuh's Theory of Engagement. Unlike existing studies that often treat AI as a peripheral tool, this work positions AI as a central, dynamic facilitator of peer learning processes. By doing so, it not only extends the theoretical understanding of AI's role in educational environments but also introduces a new model that links AI interventions directly to student retention, engagement, and academic performance.

5.9.2 Theoretical Contribution

This research adds to the literature on using AI to enhance peer-assisted learning. It provides a new perspective on AI in the learning process, showing that AI peer-to-peer support positively impacts students' motivation and performance. The study, grounded in social constructivism and networked learning, reflects modern learning environments' interactive and connected nature. The proposed theoretical model advances knowledge by illustrating how AI can promote collaborative learning, activities, and outcomes.

5.9.3 Methodological Contribution

Methodologically, the study introduces a robust mixed-methods approach that integrates quantitative and qualitative data to capture the multifaceted impact of AI on peer-assisted learning. This approach validates the study's findings and provides a replicable framework for future research. The methodological rigour of combining AI-driven data analytics with traditional educational research techniques represents a significant advancement in how academic research can be conducted in AI-integrated environments.

5.9.4 Practical Contribution

Practically, the research offers concrete, evidence-based recommendations for integrating AI into peer-to-peer learning contexts. These guidelines are grounded in the study's empirical findings and tailored to address educational institutions' specific challenges and opportunities. The research provides actionable insights for educators, policymakers, and technology developers on effectively harnessing AI to improve student engagement, grades, and retention. By addressing the practicalities of AI implementation, this work bridges the gap between theoretical research and real-world application, ensuring that its contributions are academically significant and practically relevant.

In conclusion, this research presents theoretical, methodological, and practical contributions. This work adds to the literature on AI in education, provides a sound methodological framework for future research, and offers fundamental guidance on integrating AI into peer-to-peer learning environments. These contributions also enrich the existing body of knowledge and provide implications for future educational research and practice.

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APPENDICES

Appendix 1 Site Approval

Cape Peninsula University of Technology

Office of the Deputy Vice-Chancellor: Research,
Technology Innovation & Partnerships
Bellville Campus
P O Box 1906
Bellville 7535
Tel: 021-959 6242

26 October 2023

Mr Mark Wilson-Trollip
Staff/ Student No: 183000668
Department of Business Management
Sciences

Dear Mr Wilson-Trollip

RE: SITE PERMISSION TO CONDUCT RESEARCH AT CPUT

Based on the recommendation of APPROVAL from the Faculty of Business Management Sciences Research Ethics Committee) I am pleased to support your research study "***Artificial intelligence as a facilitator of peer-to-peer learning: Effect on retention, achievement, and student belief system***". Your request to access Cape Peninsula University of Technology as a research or recruitment site, is granted.

The research study will include examining *how the architecture of AI, specifically as a facilitator of peer-to-peer interaction, can enhance student retention and academic achievement and potentially transform the student belief system?*
This research employs quantitative analysis techniques to explore student activity, academic performance, and six-year survey responses from a single Cape Town, South African university. The study adopts a longitudinal approach, observing changes over time to provide in-depth insights. The data collected from the university's academic records will focus on three primary variables:

1. *Student Retention: The research will explore student withdrawal rates from a course or program.*
2. *Academic Achievement: The study will analyse shifts in course grades pre-and post-implementation of the AI-assisted learning platform. The courses comprise Financial Management 1, 2, 3, and 4*
3. *A broad student Belief system: This investigation will explore the outcomes of sixteen historical surveys on student engagement to reflect a broad student belief system. Although perceptions are subjective, the study assumes an objective reality that can be interpreted non-biasedly. A quantifiable measure of students' experiences towards the AI-assisted platform can be obtained by applying proven frameworks to survey questions.*

This site permission covers the time-period of 25 October 2023 to 25 October 2024.

The CPUT site permission is contingent on research ethics approval as well as adhering to all the relevant CPUT policies and regulations.

The following information has relevance:
Research Ethics Approval Date: 24 October 2023
Research Ethics Approval valid until: 24 October 2024
Research Ethics Approval Reference No: 2023_FBMSREC_ST14

Permission is herewith granted for you to do research at the Cape Peninsula University of Technology.

Wishing you the best in your study.

Sincerely

Prof Dina Burger
Director: Directorate Research Development
Cape Peninsula University of Technology

Appendix 2 Permission for Academic Performance Data Collection

Cape Peninsula
University of Technology

Management & Project Management Department
Ms NB Luphondo
District Six Campus
P O Box 652 Cape Town 8000 · Corner of Hanover
and Tennant Street, Cape Town 8000
(021) 460-3928
Website: www.cput.ac.za
luphondon@cput.ac.za

30 March 2023

Dear Mr Wilson-Trollip

PERMISSION FOR ACADEMIC PERFORMANCE DATA COLLECTION IN THE DEPARTMENT OF MANAGEMENT & PROJECT MANAGEMENT.

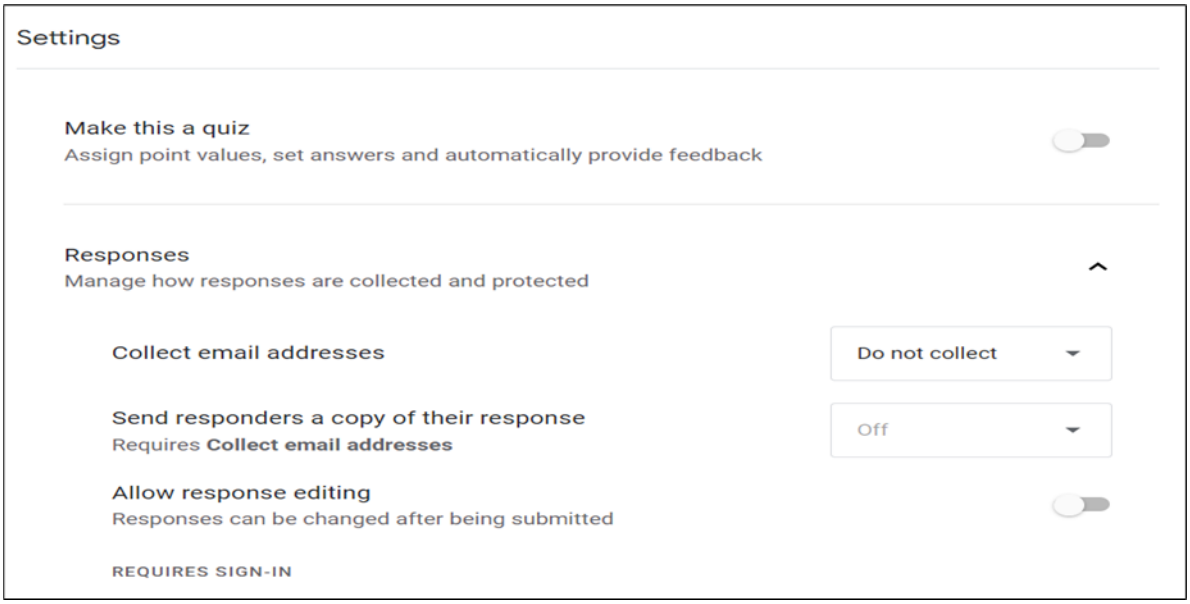
This serves to confirm that the Department of Management and Project Management grant Mr Mark Wilson-Trollip permission to conduct his research in the department and to have access to academic performance data from the departmental records, of the following subjects: subjects Financial Management 1, 2, 3, 4 and Investment Analysis for the period 2016 – 2022. He will use the data as part of the analysis for research purposes. There is no personal information required and the data will be treated with confidentiality.

Should you have any queries on the above, kindly contact the Department of Management and Project Management.

Yours Sincerely

Nobuhle Luphondo
(Acting Head of Department)

Appendix 3 Survey Settings



Appendix 4 Survey Questions

Financial Management September 2023

This questionnaire aims to investigate the role of Artificial Intelligence as a mode of learning and teaching. The collected data is to advance the current understanding of AI's educational capabilities and its alignment with pedagogical methods in the department. We are required to send regular surveys for students but we have not conducted one for colleagues and staff.

Ethics Statement:

Participation in this questionnaire is entirely voluntary. All responses will be kept confidential and anonymised. No personal identifying information will be disclosed or used for other purposes outside this study. Consent to participate indicates an understanding of these terms.

You agree to participate under these ethical guidelines by proceeding with the questionnaire.

* Indicates required question

1. How do you perceive AI's role in facilitating peer-to-peer learning in higher education? *

Tick all that apply.

- [ ] Essential
- [ ] Beneficial but not essential
- [ ] Neutral
- [ ] Ineffective
- [ ] Detrimental
- [ ] Unsure

2. To what extent does AI-enhanced peer-to-peer learning impact student retention? *

Tick all that apply.

- [ ] Significantly improves
- [ ] Moderately improves
- [ ] No impact
- [ ] Moderately worsens
- [ ] Significantly worsens
- [ ] Unsure

3. Do you believe AI enhances student academic performance? *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree
- Unsure

4. Does AI alter your perspective about peer-to-peer learning? *

Tick all that apply.

- Not at all
- Slightly
- Neutral
- Moderately
- Significantly
- Unsure

5. Does AI-facilitated peer-to-peer learning enhance student engagement? *

Tick all that apply.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree
- Unsure

Appendix 5 Scaled Coding Likeart to Questions

Term	Organisational	Psychological	Economics	Social	Environmental
No	1				
Maybe	3				
Yes	5				
Poor	1	1	1	1	1
Fair	2	2	2	2	2
Below average	2	2	2	2	2
Good	3	3	3	3	3
Excellent	5	5	5	5	5
Well		4			
Perfectly		5			
Significantly improves					4
Significantly			4		
Disagree				1	
Agree				4	
Strongly agree				5	
Reliable	4				
Highly reliable	5				
Neutral	3	3	3	3	3
Slightly effective		2			2
Effective		4			4
Moderate training		3			
Extensive training		5			
Little 4	1				
Moderate 4	3				
Complete 4	5				
Rarely	1	1	1	1	1
Somewhat	2	2	2	2	2
Sometimes	3	3	3	3	3
Always	5	5	5	5	5
Often	4	4	4	4	4
Slightly	2	2	2	2	2
Moderately	3	3	3	3	3
Not at all	1	1	1	1	1

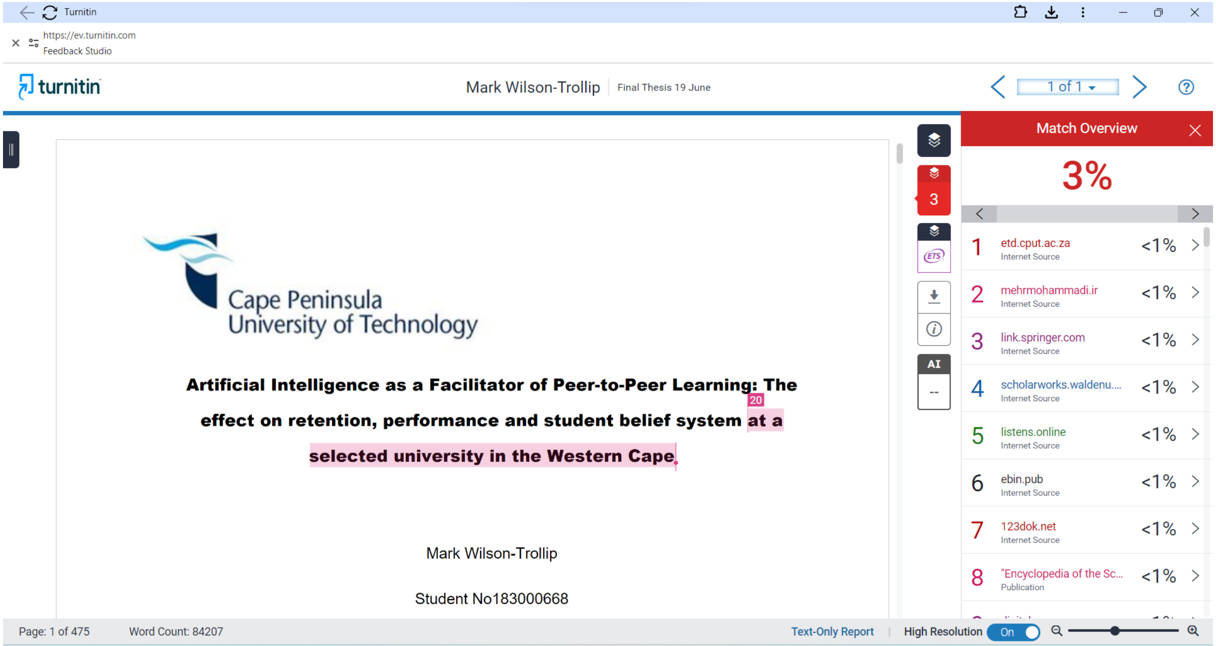
Appendix 6 Supporting Data Stored in the eSonga Repository.

Appendix 6 The link https://figshare.com/s/1f6173c54222ce2d4705 to Figshare, the eSonga Repository (Wilson-Trollip, 2024) details the following supporting appendices:

- A- The annual number of enrolled students in the dataset per year
- B- Independent Questions
- C- Category Analysis
- D- Assignment Performance
- E- Assignment Feedback
- F- Learning Analytics
- G- Algorithmic and Randomised Questions
- H- Integrated System
- I- At-Risk Intervention
- J- Analytics Dashboard
- K- Course Outline
- L- Proctoring
- M- Category Analysis
- N- Student Activity Levels
- O- Student Perception Example Questions
- P- Survey Results
- Q Lecturers Added Work
- R- Statistical Test
- S- Questions to Framework
- T- Survey from 2023
- U- Raw Data of Grades to Hours Active in Course
- V- Questions of the Survey aligned to Frameworks
- W- Histogram Graph of Questions
- X- Final Grade Sheet

- Y- Descriptive Metrics of Survey
- Z- Course Overview
- AA- Summary of Course
- BB- Ethics Approval
- CC- Site Approval
- DD- McGraw Hill Education Approval
- EE- Questions to Constructs
- FF- Example of Questions
- GG- Summary of Surveys from PDF files for themes.

Appendix 7 Turnitin Report



Appendix 8 Editors Letter

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To Whom It May Concern

This document certifies I have copy-edited the following thesis by Mark Wilson-Trollip:

AI-Facilitated Peer-to-Peer Support Influence on Engagement, Grades and Pass rates: A Mixed Methods Case Study

Please note this does not cover any content, conceptual organisation, or textual changes made after the editing process.

Best regards

Dr Patricia Harpur

17 June 2024