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The effect of artificial intelligence as a peer-to-peer support tool on engagement, grades and pass rates

Abstract

The study examines artificial intelligence's (AI) role in peer-to-peer learning and its impact on student engagement, academic performance, and pass rates. The research provided insights into how AI influences student engagement and grades through a mixed-methods approach. The research methodology adopted an interpretivist approach that includes aspects of positivism. The design employs induction using qualitative and quantitative methods. The case study operates at a longitudinal time range to study temporal performance developments. The primary data collection uses analysis of external data. The findings indicate a slight improvement in grades (3-5%), lacking statistical significance ($p > 0.05$) and a significant level of engagement (95%). This statistic raises questions about the relationship between increased engagement and tangible academic outcomes. Students show enhanced engagement through AI-driven personalised learning pathways and continuous feedback systems. Through predictive AI systems, institutions can immediately identify students facing performance-related challenges. AI peer-to-peer support must become accessible to every student without restricting it to only at-risk students. AI application policies in universities must follow mechanisms that allow adjustment for various student peer-learning environments. Partnership with AI developers remains crucial to integrate technology momentum with teaching targets. All AI peer-support policies need to include ethical criteria to maintain responsible deployment. The results suggest that while AI platforms can complement traditional peer support services, further research is necessary to understand their long-term effects on academic performance and retention. Bottom of Form

Keywords: *Academic achievement, artificial intelligence, engagement, personalisation and individualised learning, peer-to-peer support.*

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1. Introduction

Artificial intelligence (AI) integration in higher education has gained significant attention due to its potential to enhance learning outcomes and student engagement. AI-driven tools can personalise learning experiences, provide timely feedback, and facilitate peer-to-peer interactions. Despite these advancements, there is limited empirical evidence on the factors that drive young people to pursue higher education and how attitudes influence their academic intentions and performance (Malmström & Öqvist, 2018). Existing research highlights the role of technology in improving individual learning experiences (Popenici & Kerr, 2017), yet the application of AI in peer-supported learning remains underexplored.

An issue in higher education is that high student dropout rates affect individual learners and institutional performance (Copeland, 2023). Traditional support mechanisms often fail to address the diverse needs of students, necessitating alternative approaches to enhance retention and academic success. AI-driven peer-to-peer learning could provide a scalable and effective solution, offering continuous academic and social support.

This study investigates AI as a facilitator of peer-to-peer support, focusing on its impact on student engagement and performance.

2. Peer-to-peer support

Research demonstrates that peer mentoring promotes student success, especially within vulnerable learning groups (Shantini *et al.*, 2023). Terrion and Leonard (2007) say that integrating mentoring programmes into university student support services improves academic achievement and reduces dropout rates. Driving this study is understanding the correlation between peer-to-peer support functions and the most suitable type of AI support needed (Williams & Reddy, 2016), illustrated in Figure 1.

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Figure 1: Mentoring Methods adapted from (Williams & Reddy, 2016)

AI-facilitated peer-to-peer support platform approaches may build upon the paradigms in traditional frameworks while using the latest technology as a tool to cater to a diverse set of learners. Specifically, targeted academic and career development coaching methods have increased retention and improved the student's personal and educational development (Dunn & Herron, 2023). Personalised programmes may reach students and enhance engagement and performance grades.

3. Engagement as part of a student belief system

Song and Kim (2021) emphasise that understanding learning and cognitive processes necessitates an awareness of students' attitudes and participation levels. This perspective aligns with the broader view that student engagement is crucial in shaping academic success (Sandmann et al., 2008). Active participation in learning environments fosters deeper

cognitive processing, improving knowledge retention and application (Marco-Fondevila *et al.*, 2022). MacDowell and Lock (2023) further argue that participation must be examined with teaching practices accommodating diverse learning styles. Effective pedagogical strategies consider variations in cognitive abilities, prior knowledge, and learning preferences, ensuring that all students receive adequate support (Beck *et al.*, 2023). The interplay between student attitudes, participation, and instructional design highlights the need for adaptive teaching methods that integrate personalised learning experiences. AI-driven analytics can assess engagement patterns, predict potential learning gaps, and offer real-time feedback, optimising instructional strategies. As AI systems evolve, their ability to personalise learning experiences and align with various cognitive and participatory processes will be instrumental in fostering inclusive and effective educational environments (Alé-Ruiz *et al.*, 2023).

4. Grades and pass rates

A third of first-year university undergraduates discontinue their studies after their initial year. This discontinuation underscores the need for AI to enhance their academic achievement (Hutson *et al.*, 2022).

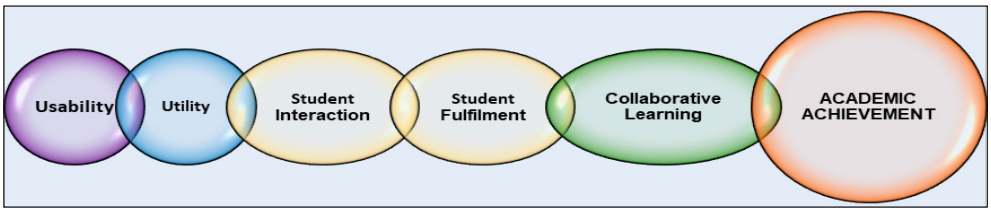

Figure 2: Modified academic achievement with AI as Peer-to-Peer Support

Figure 2 Highlights key factors influencing academic achievement, as identified in various studies (Gardašević *et al.*, 2023; Ouyang *et al.*, 2023; Bitkina *et al.*, 2020). Usability refers to how easily students navigate and use AI-assisted platforms, ensuring accessibility (Bitkina *et al.*, 2020). The term utility represents students' perceptions of how effectively AI-assisted platforms meet their academic needs. Student interaction encompasses students engaging with AI platforms and peers while learning (Gardašević *et al.*, 2023). Student fulfilment pertains to overall satisfaction with academic experiences and the perceived benefits of support (Tom Dieck *et al.*, 2024). Collaborative learning involves students working together towards shared academic goals, enhancing engagement and knowledge-sharing (Ouyang *et al.*, 2023). Lastly, academic achievement is measured by indicators such as grades reflecting overall student success (Gardašević *et al.*, 2023).

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5. Multi-faceted theoretical AI approach

The study explored the potential of AI as peer-to-peer support, illustrated in Figure 3, described by Guthrie (2023).

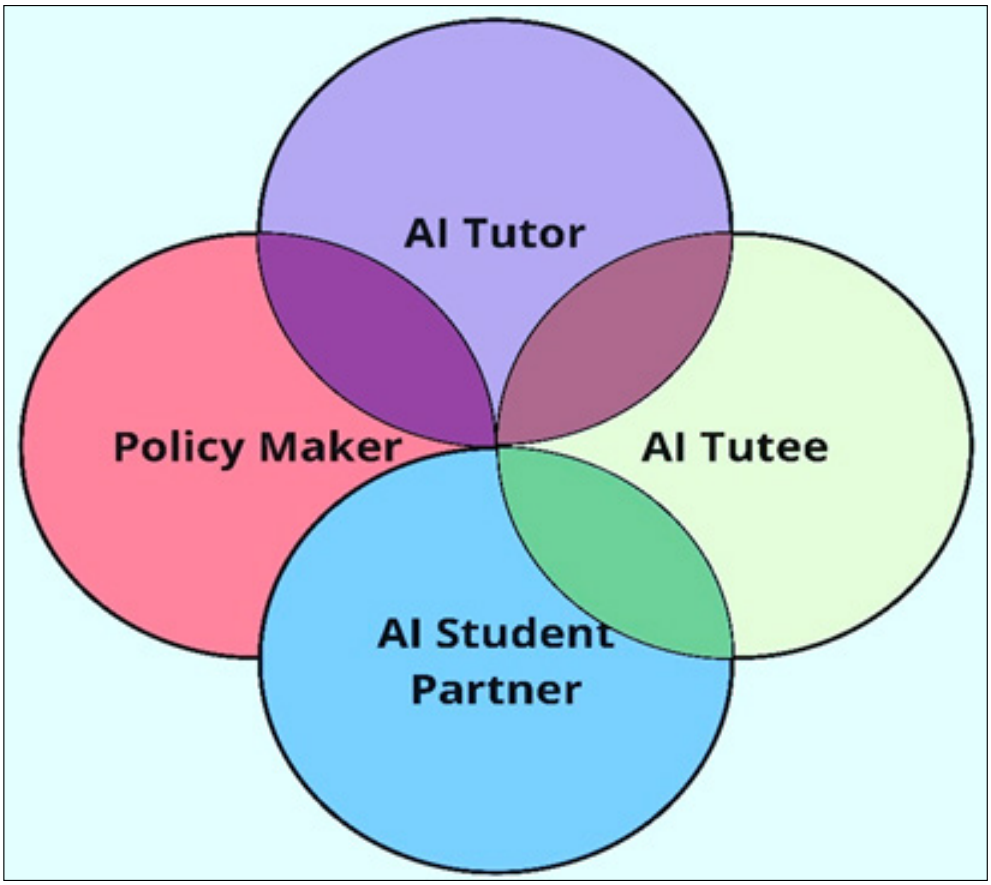

Figure 3: Framework for the Role of Peer Platforms (Guthrie, 2023)

AI can play multiple educational roles that contribute to student learning and development. An AI tutor may integrate human tutoring methods and personalised learning strategies to support individual students. As an AI tutee, AI can function as a learner, engaging in interactive academic exchanges where students refine their knowledge by teaching and correcting AI responses. As an AI student partner, AI-driven platforms can stimulate critical thinking by prompting students to analyse, evaluate, and engage in deeper discussions. Additionally, as a policy-making advisor, AI can assist in formulating and assessing academic policies by analysing data, identifying trends, and offering evidence-based recommendations for lecturer guidelines and institutional strategies.

Guthrie (2023), coupled with theoretical frameworks, helps to understand AI's role in education. The retention and attrition theory by Spady (1970), Tinto (1975), and Bean (1980) provide a framework for understanding student performance, retention and peer support. Regarding student engagement and success, Kerby (2015) stresses the need to understand the variables influencing student engagement and success.

The absence of human contact in AI-driven platforms might limit opportunities for social learning and emotional support from peers and instructors (Fan *et al.*, 2023). Institutions are designing policies to enrich undergraduate learning experiences across learning and teaching stages to improve grades (Baashar, 2022).

6. Design and methodology

Figure 4 Outlines the study's research strategy.



Figure 4: Design and Methodology

The study employs a mixed-methods case study interpretivism and positivism approach informed by the research onion framework (Saunders *et al.* 2019).

6.1 Approach

An inductive, reflexive thematic analysis (TA) approach offers advantages, as Braun & Clarke (2019) described. TA provides flexibility and fluidity in selecting co-words while maintaining data integrity and ensuring a thorough, subjectivity-aware, and comprehensive exploration of patterns within the data, ensuring that the information accurately represents real-world events and phenomena (Eisner, 2017).

6.2 Design

The study relied on an:

> *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).

Quantitative and qualitative data are analysed distinctly and integrated during interpretation (Creswell, 2014). Archival surveys form the basis for the qualitative theme interpretation. Final grades and pass rates are accessed and analysed from the 2017 to 2023 academic years. One can state that the study's data source and analysis support the chosen strategy, relying on theoretical contributions.

6.3 Participants and sampling

The data was collected from surveys and final grades from 2019 to 2023 from the institution's grades database. Factor analysis, t-tests, and correlation analysis were used to interpret the data, providing insights into the relationships between the variables.

6.3.1 Sample population

Data were collected from five courses between 2019 and 2023, resulting in 4,467 raw data entries. The survey contained 157 questions and received 13,829 responses, ensuring diversity in the dataset. Although the study focuses on one university, limiting generalisability, the response rate averaged 39% across 2,668 learners, as illustrated in Table 1, surpassing the minimum recommended threshold of 100–200 respondents (McNeish & Wolf, 2023).

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The sample size for grades included 4,363 enrolled learners, with separate groups for pre-intervention (N = 2,226) and post-intervention (N = 2,137), meeting validity requirements (Wu *et al.*, 2022).

Table 1: Sample population

Year	Population	Respondents	% Response
2019	279	118	42%
2020	879	198	23%
2021	918	405	44%
2022	616	132	2%
Total	2668	1028	39%
Average	534	206	39%

According to Yazan, 2015: 142, "(i)t is incumbent on case study researchers to draw their data from multiple sources to capture the case under study in its complexity and entirety". Yin advocates the combination of quantitative and qualitative evidentiary sources because he views them equally instrumental (Yazan, 2015: 142). The idea is to maximise the quality of the inquiry by drawing from the maximum data sources before the analysis phase.

6.4 Data collection tools

A non-obligatory survey was distributed with a strict deadline, ensuring timely data collection. The study adhered to naturalistic qualitative principles, maintaining the integrity of responses without external manipulation (Eisner, 2017).

Student final grade achievement and pass rates measured 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.

6.5 Data analysis

Yin (2009: 109) says data analysis "consists of examining, categorising, tabulating, testing, or otherwise recombining both quantitative and qualitative evidence to address the initial propositions of a study". The study captured the essence of validity and reliability while addressing the analytical procedures through thematic analysis (TA) (Yin, 2009). According to Braun and Clarke (2019), there are three broad types of TA: coding reliability; reflexive approaches and codebook approaches. This study used the reflexive approach. It involved "themes developed from codes and conceptualised as patterns" (Braun & Clarke, 2021: 39).

> *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).

Factoria is applied to the survey questions using the Likeart system and analysed statistically. The grade performance data is analysed using t-tests.

6.6 Ethical considerations

This study upholds ethical principles, including privacy protection, non-discrimination, and the exclusive educational use of data. It relies on pre-existing academic and survey records,

eliminating the need for individual consent while ensuring anonymity and minimising harm. University and ethics committee approvals were obtained, along with McGraw Hill™ authorisation. Maintaining transparency clarifies the study's purpose to the institution.

7. Results

The findings on the thematic effects of an AI-peer platform on student engagement present whether students believe the system can improve their grades and if it effectively serves as a peer-to-peer academic support service. The alleged degree of student engagement evaluates students' views on the platform and their perceived performance. Statistical results by theme, peer-to-peer, engagement, grades, and pass rates validate our understanding of the effects of engagement and performance on learning.

7.1 Reliability

This reliability section assesses how consistently the archival survey measures what it intends to measure.

Table 2: Case processing summary - Reliability

Case Processing Summary			
		N	**%**
Cases	Valid	109	46.2
	Excluded a	127	53.8
	Total	236	100.0
All variables in the procedure are based on Listwise deletion.			

This case processing summary in Table 2 provides information on the data used for the reliability analysis. Valid cases (109, 46.2%) – this was the number and percentage of survey responses used in the study. Excluded instances (127, 53.8%) – Responses were excluded because they had incomplete answers or missing data. Total (236, 100%) – the total number of cases (responses) considered. Effectively, this means that out of 236 total survey responses, 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, which could impact the robustness and representativeness of the study's findings.

Table 3: Reliability statistics

Reliability Statistics	
Cronbach's Alpha	**N of Items**
.879	4

Table 3 The reliability statistics of the survey are significant when assessing the consistency of the measurement tool used in the study. Cronbach's Alpha (α = .876) is a 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.

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7.2 Students' belief in AI influencing peer support, engagement, grades and pass rates

The average combined responses summarised in Tables 4 and 5 are students' perceived beliefs about AI peer-to-peer support and how it influences their engagement and grades.

Table 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%**	**4,42%**	**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 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	71,62%	21,26%	3,57%	3,37%	100,00%
Total	**83,62%**	**12,98%**	**1,83%**	**1,56%**	**100,00%**

Figure 5, compiled from Table 4, shows the students' perceptions regarding the impact of AI on three main combined areas: peer-to-peer support, engagement, and achievement.

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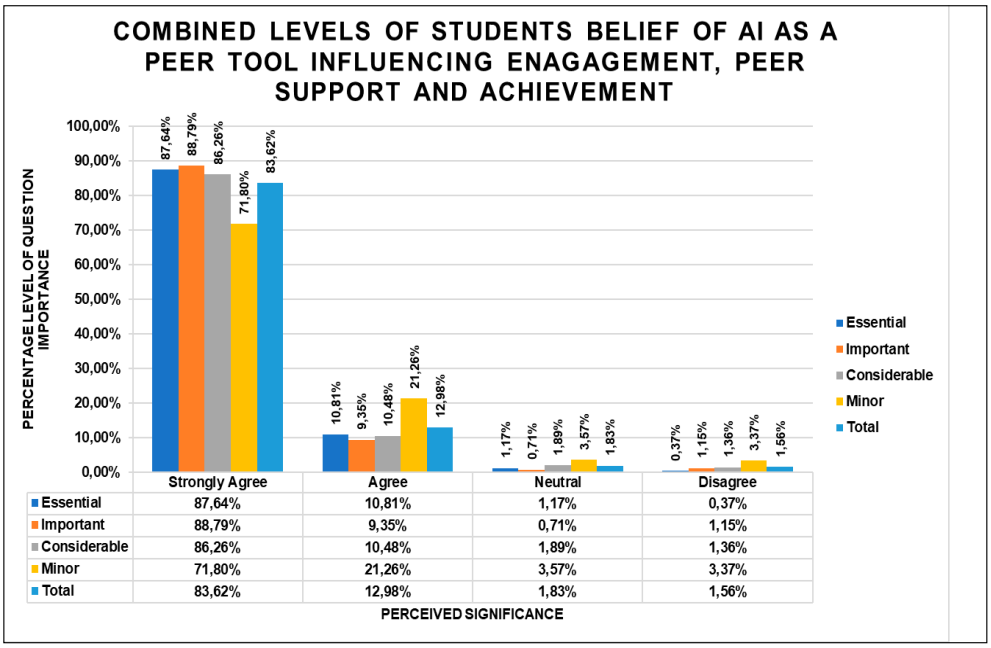

Figure 5: Combined perception of AI peer-to-peer support

The students' responses are categorised 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) and Bean's (1980) framework: *essential; important; considerable* and *minor*. These allocations emphasise AI factors directly affecting student learning and success:

- 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% show that AI peer-to-peer support has almost no importance and impact on student engagement, peer-to-peer, and achievement.

Perception portrays a preferred attitude that strongly agrees with AI's importance as a peer support tool.

7.3 Peer-to-peer support

It is reasonable to evaluate the students' use of AI peer-to-peer support to identify their academic patterns. The connection between the two areas is that if the students' perceptions of their capability and the worth of the work are congruent, their participation in AI peer-to-peer support programmes should be enhanced. The perceptions influence students' attitudes towards persistence and the implementation of the peer-support system, as well as their results.

Figure 6 and Table 6 show the student's views on the effectiveness of an AI peer-to-peer support system. The data categorises responses into four levels of agreement: *strongly agree, agree, neutral*, and *disagree*, with subcategories of *essential, important, considerable*, and *minor*.

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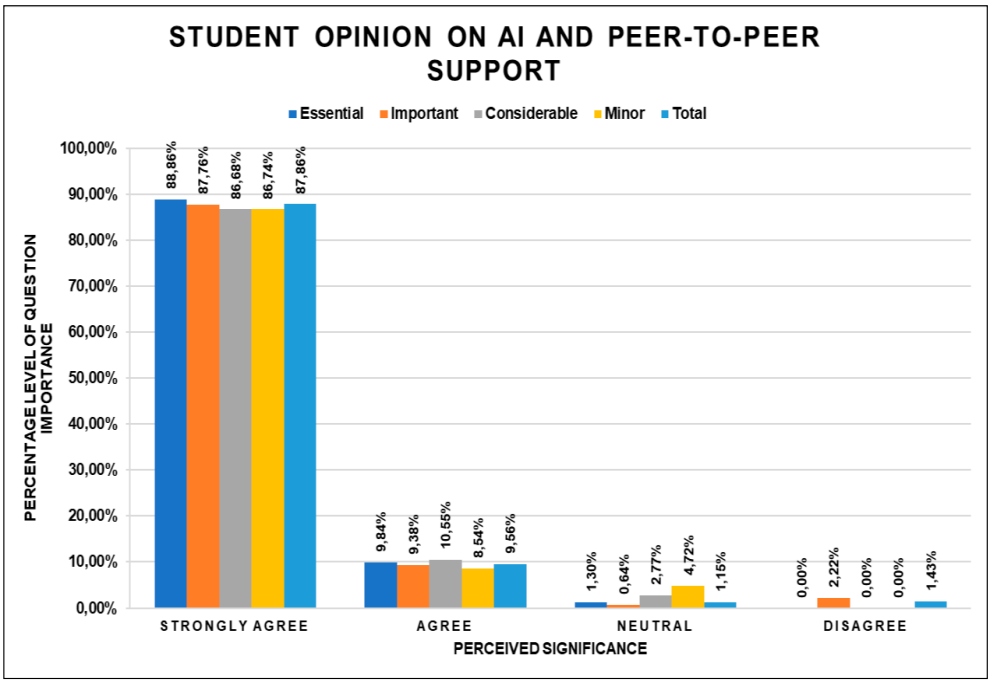

Figure 6: Student opinion on AI and peer-to-peer support

Table 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. 88.86% consider it essential, 87.76% important, and 86.68% considerable. This response shows that there is a firm agreement on the importance of the platform. In the agree category, 9.84% find it essential, 9.38% important, and 10.55% considerable. This result means that although a minor group may not consider it crucial, they still appreciate it. The neutral responses are scarce, with only 1.15% in total, meaning that most students have a clear stance on the platform. The disagree category has the lowest percentage, thus showing a shallow level of disagreement.

The survey results indicate that students perceive the AI-peer platform positively and appreciate it as a valuable peer-to-peer support tool.

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7.4 Engagement

Understanding how AI can affect students' engagement, attitude, motivation, and long-term knowledge is fundamental (Tinto, 1975). Customising the learning experience is one way of keeping students engaged and is more efficient and effective than the conventional ways of teaching (Han & Ellis, 2020; Taylor *et al.*, 2021). A possible way to customise the learning experience is through an AI peer-to-peer support platform.

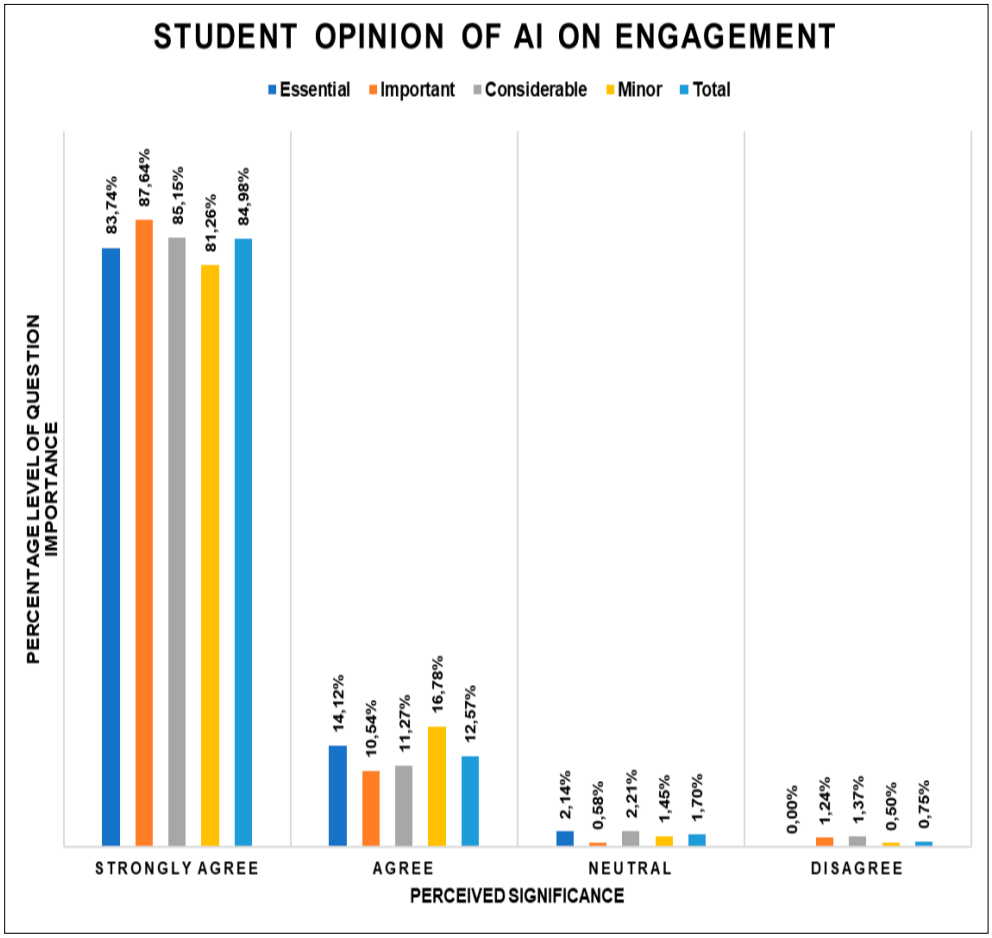

Figure 7: Student opinion of AI on engagement

The distribution of the categories in Figure 7 and the responses are provided by Table 7, which illustrates the thematic findings of the student's perceptions.

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Table 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 %

The responses are categorised into four levels of agreement: *strongly agree, agree, neutral*, and *disagree*, further breaking into *essential, important, considerable*, and *minor*, highlighting the relationship between question importance and student perception of significance.

84.98% strongly agree on the essentiality of the AI platform in enhancing engagement. Specifically, 83.74% consider it essential, 87.64% important, and 85.15% considerable. This result indicates a strong consensus on the positive influence of the AI platform on student engagement. The agree category is lower but still reflects support while 14.12% of students consider the platform essential, 10.54% important, 11.27% considerable, and 16.78% minor. 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 disagree category has the lowest percentages, indicating minimal opposition to the platform.

The data reveals a strong positive reception towards the AI platform's impact on student engagement.

7.4.1 Correlation matrix

Table 8: The correlation matrix reveals a determinant value 0.078 between the variables. It implies that students' interactions with the platform would facilitate their engagement and the relevance of the content on the platform.

Table 8: Correlation matrix

Correlation
Matrixa a. Determinant = 0.78

The value indicates that variables in the study related to AI's role in peer-to-peer learning are not entirely independent.

7.4.2 KMO and Bartlett's Test

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

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Table 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 Measure: The KMO value of 0.789 implies that the variables are close enough to warrant steps for running the factor analysis. This measure suits this kind of statistical analysis. Bartlett's Test of Sphericity: The Chi-Square value is 270.307 with 6 degrees of freedom, and the significance level is less than .001. This Chi-square indicates that the variables are significantly correlated; their relation has a natural, meaningful pattern.

These test results indicate that the data is appropriate for factor analysis and that there are significant relationships among the variables.

7.4.3 Commonalities

In the context of the study, commonalities are significant. Table 10 shows the variance percentage in each variable accounted for by the extracted factors. This percentage indicates how well the factors represent each variable.

Table 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.		

There are two types of commonality, namely:

- Initial commonalities are set at 1.000, assuming all variance in each variable is explainable before the factor analysis.
- Extraction commonalities-Values like .835 and .833 suggest that the factors explain a large portion of the variance in how accessible online classes are and attendance in the last four weeks.

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. High commonalities indicate a robust factor model. This robustness captures the vital elements influencing how AI affects peer-to-peer learning.

While high commonalities are reasonable, they do not guarantee that the factors are the most meaningful or the only influences. For variables with lower commonalities, other factors not identified in the analysis may play a role.

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7.4.4 Total variances

The Total Variance Explained, shown in Table 11, offers meaningful variability in the data that is considered valuable.

Table 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.						

The factors identified in the analysis explain variability, where each represents a specific aspect or dimension of the data:

7.4.4.1 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, suggesting it is necessary to understand how AI facilitates peer-to-peer learning.
- 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, indicating that these factors fully account for the variability in the dataset.

7.4.4.2 Factor extraction

The extraction total is a single value in Table 11 as 2.988. It comprises two sets of values, namely

- % of Variance, which is the percentage of variance explained by each component after extraction. For the first component, it is 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, accounting for a nuanced view of AI's role in peer-to-peer learning.

The Total Variance section is central to understanding the significance and impact of different factors identified in the study.

7.4.5 Component matrix

The component matrix - Table 12 - Meaningful insights are provided from the factor analysis.

Table 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 the survey) relates to the identified factor(s):

- 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 loading of .914 is highly associated with this component.

The analysis focuses on understanding how this overarching factor impacts peer-to-peer support facilitated by AI. 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. The Component Matrix of the analysis identified significant components: participation, ease of use, barriers to attendance, and perception towards online learning.

7.4.6 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 13, making this analysis not applicable:

Table 13: Rotated component matrix

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

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One component was extracted, suggesting that one theme or pattern can explain most variability in performing rotation, revealing a simplified yet strong pattern in the data related to AI's role in peer-to-peer learning. No rotation is possible: Since there is only one component, there is nothing to rotate. Rotation makes sense when there are multiple factors.

Table 14: 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 confirm significant correlations among variables.
Commonalities	High extraction communalities indicate factors that capture variability.
Total variances	The first component (74.710%)
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 patternb related to AI and peer-to-peer learning.

Table 14 validates and summarises the survey findings and implications of the various statistical analyses. The study has indicated a correlation between the variables reconsidering the use of AI in peer-to-peer support as a learning tool.

7.4.7 Descriptives

Table 15 describes the distribution and characteristics of responses for the main factor (aspect) measured in the surveys.

Table 15: 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

The mean (3.91) and the median (3.67) suggest that participants had a decisive attitude towards the survey questions, ranging from 1 to 5. The narrow 95% confidence interval (3.80-4.02) indicates that the sampling mean is accurate, and the standard error is low at 0.057. The 5% trimmed mean (3.98) suggests that outliers do not significantly impact the data. The low variance (0.770) and standard deviation (0.877) indicate moderate response variation. The negative skewness coefficient (-0.940) suggests that the responses skew slightly toward

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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 the data is credible and accurate by thoroughly accounting for response patterns and distribution forms.

The final analysis involved 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.

8. Grades and pass rates

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.

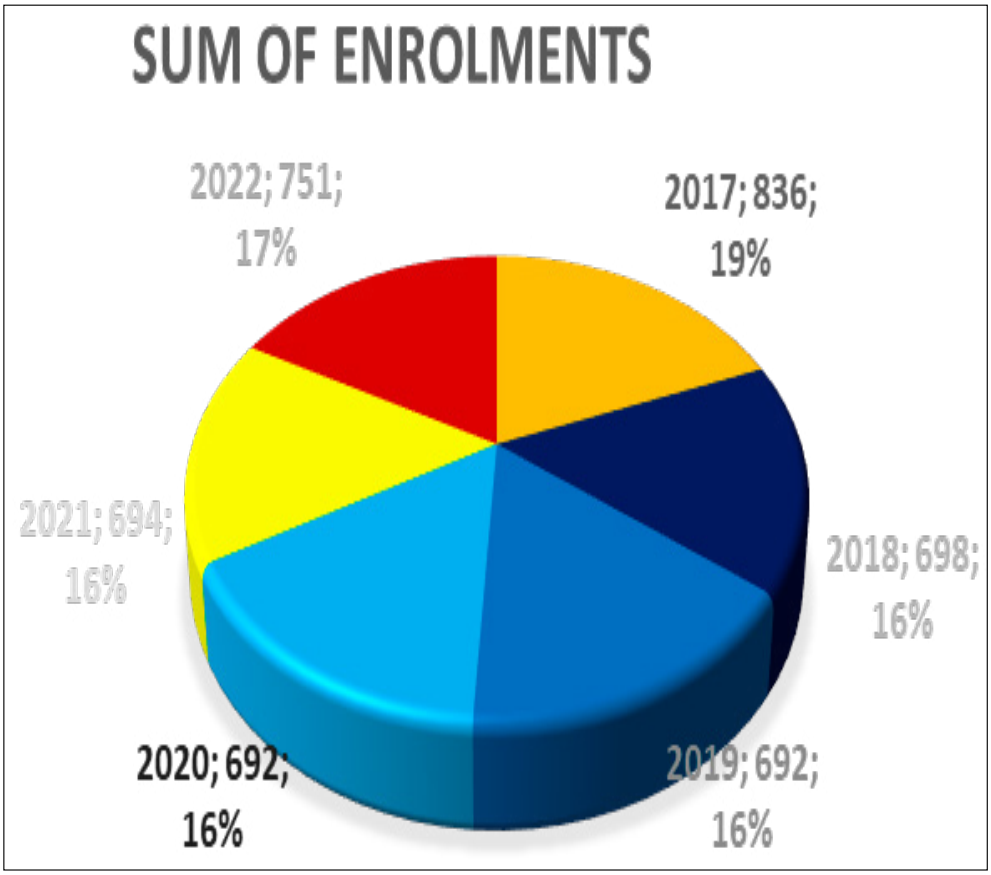

Figure 8: Total enrolment figures by Year: 2017-2022

Figure 8 shows the enrolment of students from 2017 to 2022. The chart shows that enrolment was highest in 2017 at 836 (19%). The enrolments 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% share. In 2022, there was an increase to 751 enrolments, which was 17%.

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The data details students' enrolment, 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 16.

Table 16: 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	0,009659349	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

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.

Table 17 summarises the pre-and post-intervention pass rates and final average marks per course, financial management 1, 2, 3 and 4.

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Table 17: Financial management enrolments, pass rates and grades

Group: Financial Management 1 (FM1)

Year	Enrolments	Passed	Pass Rates	Average Final Grades
Pre-intervention				
2017	289	201	69.55%	62.15%
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 (FM2)

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 (FM3)

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 (FM4)

Year	Enrolments	Passed	Pass Rates	Average Final Grades
Pre-intervention				
2017	80	61	76.27%	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 enrolment trends, pass rates, and average final grades. The outcomes of the data analysis are:

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- Financial management 1 (FM1) – enrolments increased post-intervention to 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 low, with minimal improvement from 50.10% in 2020 to 51.71% in 2022.
- Financial management 2 (FM2) – 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 (FM3) – 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 (FM4) – 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.

The data shows that the intervention had a varied impact across different course levels. FM3 experienced the most significant positive changes in pass rates and final grades, while FM4 also showed improvement. Financial management 1 and 2 had more fluctuating results, with FM1 showing some enrolment recovery but inconsistent pass rates and grades. The intervention seems to have impacted higher-level courses, namely FM3 and FM4. The data suggests a correlation between the intervention and improved academic performance, especially in advanced classes.

8.1 Grades and student perception

Figure 9 and Table 18 Illustrate the perceptive thematic findings of students' beliefs that the AI peer-to-peer support platform affects their grades.

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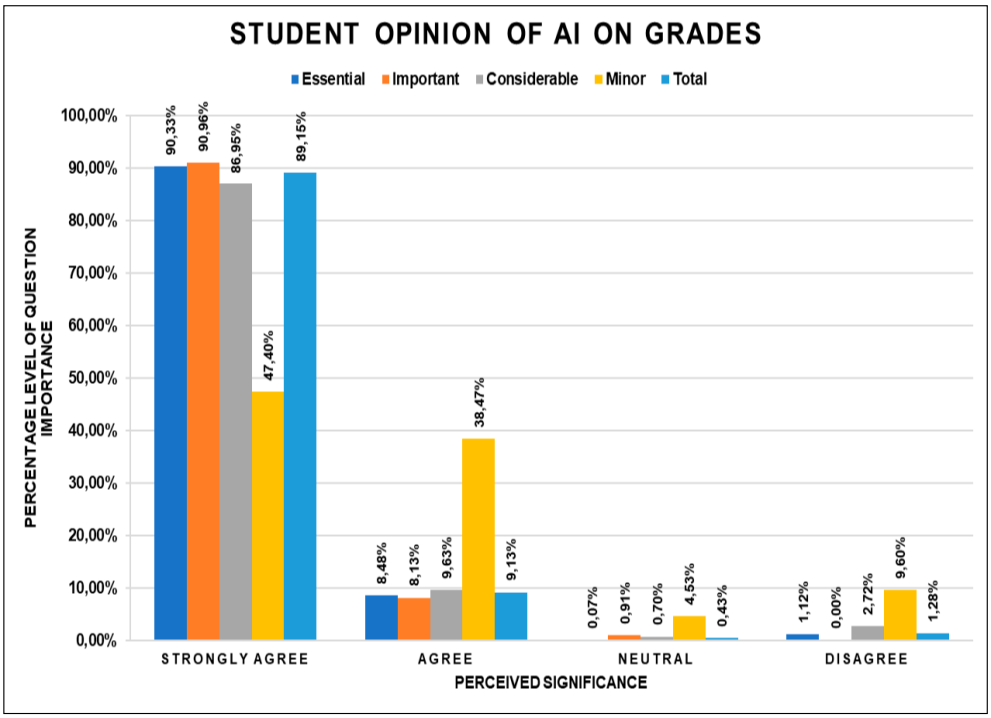

Figure 9: Student opinion of AI on grades and pass rates

Table 18: 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 %

The responses are categorised into four levels of agreement: *strongly agree, agree, neutral,* and *disagree*. The questions were subdivided into *essential, significant, 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, and 86.95% considerable. 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, and 9.63% considerable. This support indicates that

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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 of the AI platform's influence on their grades. The disagree category contains the lowest percentages, indicating minimal opposition. No students disagreed with the platform being Important.

The data highlights a robust reception toward the AI platform's impact on grades, with most students recognising its necessary role in academic performance. An additional two-tailed t-test, assuming unequal variances and statistical analysis, is undertaken to determine if the perceived positive influence of the AI platform on engagement affects grades.

Table 19: Summary of all course 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

The two-tailed t-test compares average grades and pass rates between pre-and post-intervention categories by course, as illustrated in Table 19. For all classes, 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.

The intervention did not lead to a statistically significant grade change for any of the financial management courses analysed (FM 1 to 4). This insignificance means that any observed differences in mean grades before and after the intervention are due to random variation rather than the intervention itself. Students, however, believe that more prolonged engagement with the platform leads to better individual performance.

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8.2 Pass rates

T-tests were conducted on the average pass rates, as shown in Table 20, to ascertain statistical significance when using the platform and to summarise if there is any change in the pass rates.

Table 20: Summary of all courses 6 6-Year t-test pass rates 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.	0,7544651	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

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.

The data suggests that introducing the AI platform did not result in a statistically significant impact on pass rates across the courses.

9. Discussion

Using AI in a teaching-learning environment improves student interaction by providing peer support, as Arco-Tirado *et al.* (2020) and customising learning models (Zhao *et al.* 2021). 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 (Gardašević *et al.*, 2023). Predictable prompts help keep learners engaged and moderate potential variation to maintain knowledge flow, cut distractions, and improve memory (Lainjo, 2023). Students learn interactive social skills through peer group assignments, competitions, and other required social learning activities (Weitekamp *et al.*, 2020). Individualisation helps students comprehend, recall, and remember course content (Slavin *et al.*, 1984). This way, availing an AI tool creates a supportive, engaging, and stimulating learning environment, allowing for content variation that depends on the student's learning ability and ensuring that the feedback given is always timely.

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9.1 Engagement

The study showed 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. Engagement initiated by Tinto (2017) and Bean (1980), and the Retention Theory and the Theory of Attrition emphasise the role of group interaction. 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. The optimistic view of AI in learning shows that it may beneficially impact student achievements. These findings underscore the importance of AI in facilitating peer relationships and enhancing academic achievement (Zhao *et al.*, 2021).

9.2 Grades and pass rates

Although the AI platform did not result in a statistically significant improvement in pass rates, it 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 (Ortega-Ruipérez, 2022). Self-control increases intrinsic cognitive load and reduces excessive strain. AI platforms should be designed with user-friendly interfaces and real-time feedback to enhance academic achievement, foster peer relationships, and promote collective problem-solving in collaborative learning environments. Human-centred AI systems could improve academic success by considering the motivational and emotional aspects of learning (Sharma *et al.*, 2023). They provide customised support and adaptive feedback and reduce anxiety, promoting a supportive learning environment that improves students' performance (Sharma *et al.*, 2023).

9.3 AI peer-to-peer support

The AI adaptive platform aims to improve student interaction with the university system. This interaction enhances relations and student involvement (Li & Xue, 2023). Improved involvement benefits individual student learning, especially in acquiring new knowledge (Vygotsky, 2011). Within systematic learner behaviours and communication activities, AI peer-to-peer support enhances the learning environment's psychological, social, economic, and organisational limitations (Wentzel & Wigfield, 1998). 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.

10. Conclusion

All students should be allowed to follow specific paths and receive 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. All students should have access to AI peer-to-peer support, not limited to those at risk. This inclusion is a proposed policy recommendation. 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 should consider the kinds of AI

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learning applications to ensure platforms adapt to various forms of peer support and knowledge acquisition. Interaction with the developers of AI is crucial in developing appropriate platforms that will enhance the delivery of educational objectives supported by AI systems. Integrating ethical aspects into the AI peer-to-peer support policy is integral to the AI peer-to-peer support implementation decision.

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