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Harnessing AI for peer-to-peer learning support: Insights from a bibliometric analysis

Abstract

This study investigates the current use of artificial intelligence (AI) for peer-to-peer support through a bibliometric analysis of 1113 records based on co-words. The research employs a four-phase exploratory design that involves co-word search, data charting, and result summation. It uses an inductive, relevant, and reflexive thematic approach (TA). The theoretical foundation is grounded in retention, attrition, and learning theories, including personal, social, emotional, constructive, and humanistic theories. The analysis aims to determine whether institutions leverage AI for peer-to-peer learning as part of peer support. The findings reveal a significant gap in direct research on AI's role in peer-to-peer support, underscoring the need for future studies on its impact on learning customisation, socio-emotional learning, and ethical issues in education.

Keywords: *Academic achievement, Artificial Intelligence, Student Retention, Attrition, Socio-emotional Learning, Personalised Learning, Individualised Learning, Peer-to-Peer Support, Constructivist Learning, and Humanistic Learning theories.*

1. Introduction

Peer-to-peer learning enhances critical thinking, creativity, and social skills, influencing higher education grades, pass rates, and retention (Topping, 2005; Carini *et al.*, 2006; Roscoe & Chi, 2007). Understanding the influence of artificial intelligence (AI) on retention, attrition, and learning competencies can lead to advanced educational technologies.

1.1 Background and significance

Dos Reis and Yu (2018) emphasise the value of traditional peer-to-peer support *programme*s' integration of students into classrooms. Peer-to-peer support involves mentors aiding recipients in their academic, professional, and personal journeys (Etzkorn & Braddock, 2020). Fernandez-Martin and Hervas-Torres (2020) highlight peer-to-peer tutoring's role in improving performance and retention. Personalised, socio-emotional, constructivist, and humanistic learning theories significantly impact student outcomes

(Mills *et al.*, 2006; Sormunen *et al.*, 2020; Marco-Fondevila *et al.*, 2022). Applying Bean and Metzner's (1985), & Tinto's (1975) attrition, retention and involvement theories underscore the significance of personalised, socio-economic, constructivist and humanistic learning competencies in peer-to-peer support structures.

1.2 The importance of peer-to-peer support

Team learning or support is a form of learning that focuses on students' collaboration, making the class lively to the extent of facilitating learning. It also assists in the development of individuals' analytical skills and critical thinking skills since the students are required to defend their opinions and argue with their peers. It enhances the students' academic achievement and social and emotional well-being and prepares them to manage various issues they may encounter in society (Topping, 2005).

1.3 The role of AI in peer-to-peer support

AI may enhance peer-to-peer support by offering specific help and material based on the student's needs. AI-based applications could help identify the correct study partners and tutors for students, track the student's progress and give instant feedback. This technology may identify students likely to drop out or perform poorly and provide measures to ensure they return on time and enhance their performance (Han & Ellis, 2020). Thus, applying AI in peer-to-peer support roles could improve the programs' quality, productivity, and, as a result, the student's achievements and overall retention rates.

1.4 Research question

Does the literature show that AI facilitates peer-to-peer support? This question determines whether institutions have embraced AI peer-to-peer learning as a support tool. It may have implications for developing enhanced educational technologies that positively impact the students' achievement, enrolment, and learning experiences. By examining the current state of research, this study aims to identify gaps and potential areas for further investigation, contributing to the effective integration of AI in educational settings.

2. Theoretical framework

The study reviews the literature, exploring AI peer-to-peer support relationships as a form of university peer support, using Tin's (1975) and Bean's (1980) retention and attrition theories and four learning theories, personalised, socio-economic, constructivist and humanistic.

2.1 Personalised learning

Personalised learning theory tailors education to meet individual student needs, enhancing relevance and engagement. AI could support personalised learning by adapting to each student's pace and learning style, which improves academic integration and retention. Han and Ellis (2020) note that personalised learning networks promote deep learning approaches and positive perceptions of course design integration. Tinto's (1975) model highlights the importance of socio-emotional engagement for retention, suggesting that AI-supported personalised learning may enhance education's academic and emotional aspects.

2.2 Socio-emotional learning

Socio-emotional learning (SEL) focuses on developing social and emotional skills crucial for student engagement and retention. Tinto (1975) emphasises that social integration influences learning and retention. AI tools, such as social annotation activities, may enhance social presence and cohesive communication, thereby positively impacting cognitive presence in online learning (Cui & Wang (2024). Goldoni *et al.* (2023) noted that teaching socio-emotional skills through technological resources could lead to positive learning, social inclusiveness, and constructivism.

2.3 Constructivist learning

The constructivist learning theory focuses on participation and learning by associating new knowledge with prior experience. According to Rufii (2015), constructivist strategies entail learners' interaction and involvement in content. As postulated by Tinto (1975), students will have a high propensity to continue their university studies if they engage in the learning process. Chapman (2011) states that participation, social presence, and collaboration are the factors that support student motivation. AI peer-to-peer support can potentially foster initiative-taking and interactive learning processes for students following constructivist theory and help them build and enhance knowledge (Chapman, 2011).

2.4 Humanistic theories

Humanistic learning theory is based on the growth and enhancement of self and promoting a healthy learning climate (Li and Ma, 2023). Humanistic theories, for instance, stress the importance of content and the capacity of the learner to engage in the learning process. Artificial intelligence as peer-to-peer support may help develop these aspects by designing individual learning paths and deepening the learners' understanding, thus leading to better results and learning outcomes.

These theories provide the backdrop of this research to examine how AI supports peer-to-peer learning and look at areas for improving the learning environments for improving learners and their retention rates.

3. Research design and methodology

Artificial intelligence's application in peer-to-peer learning support is examined through a review of 1113 articles and the use of bibliometric analysis, co-words, themes and trends identification (Donthu *et al.*, 2021). From the literature, can it be concluded that AI enhances peer-to-peer support? Thus, the given analysis focuses on the values of AI peer-to-peer support for learning that have been deemed central to a scholarly discussion (Alonso-Muñoz *et al.*, 2023). It examines peer-to-peer support in AI and the sources used within the research. It establishes the frequency of the main co-words, themes, trends, and topics of the educational material concerning the current knowledge of AI and peer-to-peer support. The design and co-word analysis enables the categorisation of significant themes concerning AI within the context of peer-to-peer learning. It helps identify changes and trends in transforming traditional forms of knowledge that use AI and teamwork (Donthu *et al.*, 2021). These trends are significant in this investigation's understanding of whether institutions harness AI peer-to-peer learning support.

3.1 Four-phase exploratory design

The primary method for exploring the role of AI in peer-to-peer support involves performing a bibliometric coupling of co-words. Figure 1 illustrates the process from identifying the problem to reporting the results. Chang, Huang and Li (2015, 2071–2072) state that:

> *Trend analysis in research subjects assists researchers in planning their research direction and predicting research trends. Thus, trends in research subjects have been of considerable concern for academics.*

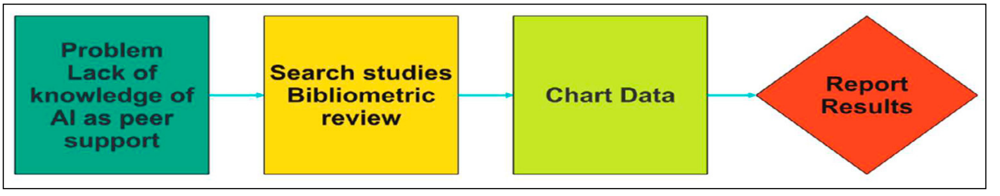

Figure 1: Basic design

The process follows an adapted iterative four-stage approach (Pham *et al.*, 2014):

1. Problem identification

   The study explores the gap in knowledge regarding the use of AI as peer-to-peer support in educational settings. This phase involves recognising the lack of research on how AI facilitates peer-to-peer learning support.

2. Search and bibliometric review

   The study conducts a literature search and bibliometric analysis, reviewing studies and articles relevant to AI and peer-to-peer support. Bibliometric methods are employed to analyse co-words, identifying research trends and themes.

3. Data charting

   The study follows a rigorous approach to map the data and portray the density and connections of the most repeated co-words, themes, and tendencies related to AI and peer-to-peer support.

4. Reporting and discussing the results

   The study summarises, discusses the main findings, and analyses the gaps in the literature. This phase also outlines the directions for future research to expand the understanding of the use of AI in peer-to-peer support. The review analyses the co-words terms from the literature and helps to determine the areas lacking a specific subject or field of research to guide future actions (Donthu *et al.*, 2021).

A conceptual model of AI peer-to-peer support from retention, attrition and learning theories by Tinto (1975) & Bean (1980) and an inductive thematic analysis build on the proposed study's review.

3.2 Inductive, reflexive thematic approach (TA)

The study uses an inductive, relevant, reflexive thematic analysis (TA) to answer the research question, as described by (Braun & Clarke, 2019). The rationale for selecting this methodology is as follows:

1. **Flexibility and fluidity:** TA allows some form of adjustment to the co-words in the process. For instance, one can remove or add terms, which is beneficial for the analysis.
2. **Integrity of data:** This approach ensures that information is authentic, portraying events and items as they happen in the real world (Eisner, 2017).
3. **Depth of analysis:** By demanding comparisons, presumptions, prejudices, and perspectives when selecting the co-words, the method ensures the detailed and intensive study of the data.
4. **Cyclic procedures:** The process involves coding to identify the categories of the data collected, then interpreting the data and reflecting on the coded information. Thus, going back and forth in the analysis improves the process, and the data's themes are valid.
5. **Subjectivity acknowledgement:** Reflexive TA recognises subjectivity in the search process cannot be eliminated.
6. **Comprehensive exploration:** One of the most common forms of inductive analysis is thematic analysis, which simplifies the identification of data patterns. This approach ensures the study remains grounded and sensitive to its context and the dynamics of the collected data, leading to more relevant research findings.

3.3 Ethical clearances

The faculty research and ethical committee of the Cape Peninsula University of Technology approved this bibliometric study (Research ethics approval reference no: 2023_FBMSREC_ST14). Additionally, the senior vice-president (product) at McGraw Hill Education granted permission on 31 March 2024 to access their software for research purposes.

3.4 Conceptual framework

Concerning the theories outlined in the study, the conceptual framework explains how AI can support student learning through peer-to-peer communication. The framework uses an independent variable, the AI peer-to-peer support, and dependent variables, the humanistic learning theory, constructivist learning theory, personalised learning theory, and socio-emotional learning theory, to identify their link, capabilities and orientation.

3.4.1 Visual representation of the framework

The conceptual framework, depicted in Figure 2, implies integrating the learning process subsystems such as peer help and AI peer-to-peer support (Halverson & Graham, 2019; Balilah *et al.*, 2020). Peer-to-peer support aids personal socio-emotional learning, constructivist learning, and the humanistic application theory, which affects retention.

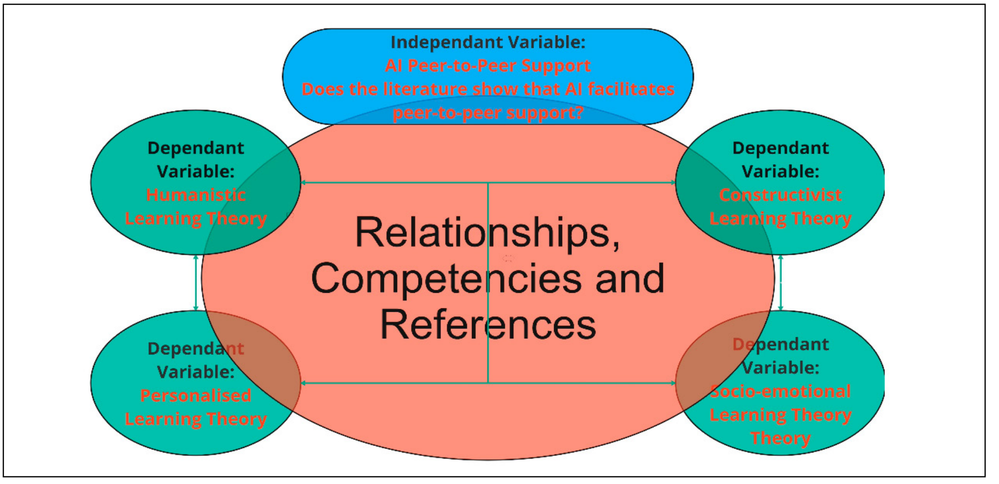

Figure 2: Conceptual Framework AI peer-to-peer support

- **Central component:** Concepts, relationships, competencies, and references encapsulate the interconnectedness of the learning theories with AI peer-to-peer support.
- **Independent variable:** This is positioned at the top, indicating the primary focus of the inquiry.
- **Dependent variables:** Located around the central element, all connected to the central idea, showing how they are interconnected and contribute to the concept of AI in peer-to-peer learning.

The proposed framework implies that AI peer-to-peer support (the independent variable) should be embedded in the learning theories (dependent variables) with consideration of Tin's (1975) and Bean's (1980) models of retention and attrition, respectively.

3.4.2 Independent variable: AI peer-to-peer support

This variable determines whether the literature indicates that AI is used for peer-to-peer support.

3.4.3 Dependent variables and theories: Personalised learning theory

Applying AI in learning potentially offers personalised learning solutions to the learner's needs, thus making learning more effective and fun. In Tin's (1975) model, retention is a function of academic and social integration.

3.4.4 Socio-emotional learning theory

AI tools might help with social presence and interaction, the cornerstone of socio-emotional learning. Tinto (1975) notes that integration is crucial to understanding and retention because it promotes students' participation and success.

3.4.5 Constructivist learning theory

Constructivist learning strategies require the learner's participation and link to knowledge. AI peer-to-peer support may have the potential to increase communication and engagement, prompting people to contribute actively to the design of courses that are vital to constructivism.

Tinto's retention theory focuses on students' engagement in the academic process. Using constructivism with the help of AI could enhance learners' motivation and interest in the learning process through active learning strategies.

3.4.6 Humanistic learning theory

Humanistic learning deals with the development of the learner and establishing an effective learning atmosphere. AI peer-to-peer support may also help by giving feedback and delivering individual support, which could help in this regard and thus improve academic achievement. The conceptual model presented in this paper incorporates these theories to explain the relations with AI peer-to-peer support.

3.4.7 Theoretical underpinnings

Tinto (1975) indicated that these learning variables are relevant in creating and assessing peer support as an intervention strategy to improve retention.

Table 1: The research question connected to the theories and AI's role

RQ1: Does the literature show that AI facilitates peer-to-peer support?			
Framework	**Theoretical underpinning**	**AI's role**	**References**
Personalised Learning	Tinto (1975) - academic and social engagement.	Could tailor learning to individual needs.	Tinto (1975); Han and Ellis (2020); Fokkens-Bruinsma *et al.* (2021)
Socio-Emotional Learning	The importance of social integration and engagement theories.	May enhance social presence and interaction through AI tools.	Goldoni *et al.* (2023); Cui & Wang, (2024)
Constructivist Learning	Active participation and connection to knowledge, constructivist strategies.	Potentially facilitates collaborative learning environments.	Chapman (2011); Rufii (2015)
Humanistic Theories	Focus on individual growth and a positive learning environment.	May improve grades and personalised learning experiences.	(Li and Ma, 2023)

Table 1 summarises the learning variables interconnectedness nature of the conceptual framework, their theoretical underpinnings, and AI's role in each element, as well as references supporting these connections to the research question (Tinto, 1975; Bean, 1980; Bork, 1999; Davidson & Wilson, 2017; Tight, 2019). This interconnectedness directs the research question, the study's design and the method (Bean & Metzner, 1985; Tinto, 1975).

3.5 Data collection

Anchoring this study are the guidelines for secondary research as outlined by Pham *et al.* (2014). Out of the 1,113 articles, the selected articles contained 17,045 keywords from the title and abstract fields in the databases. These terms were captured and analysed by recording 635 co-occurrences with at least ten iterations.

Despite contributing a bibliometric literature review on using AI peer-to-peer support for learning, the data collection has some limitations in its method arising from secondary data and bibliometric analysis. These limitations include the possibility of the reviewer's preference in the selection of literature, the co-words, the transferability of the findings to other educational and cultural settings, and the dynamic nature of AI. Recognising these limitations in the method helps inform future research to fill these and improve the integration of AI in education.

3.6 Data analysis: Bibliometric analysis

In this case, a bibliometric coupling literature review searches AI's role in peer-to-peer learning using co-words. The author 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.*, 2021, para. 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). According to Donthu *et al.* (2021), a co-word analysis can be used as a supplement to enrich understanding of 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 *et al.*, 2015),. Using co-word analysis can thus help researchers elaborate on the content of each thematic cluster. Secondly, "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 potential limitation of this study is its reliance on bibliometric analysis, which, while valuable for identifying trends and gaps in existing literature, may not capture the nuanced, qualitative aspects of AI's impact on peer-to-peer support. This approach primarily focuses on published works, potentially overlooking emerging practices or insights from educational settings not yet reflected in the literature.

3.7 Data analysis: Hermeneutic analysis

In the present search, the analysing activity is hermeneutic and systemically follows the steps outlined by Boell and Cecez-Kecmanovic (2014) regarding contextual analysis to explore if institutions harness AI peer-to-peer support for learning. It is necessary to look further into AI's improvements in learning (Li *et al.*, 2020; Xia *et al.*, 2022).

The search 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® for mapping and their interpretation of the results. VosVeiwer® is software that builds and analyses bibliometric networks like journal networks, researcher networks, or individual publication networks, constructed from citation relation, bibliographic coupling, co-citation or co-authorship. The functionalities of VOSviewer include text mining, where it is possible to build and display co-occurrence networks of co-existing terms derived from the body of scientific literature, databases and sources. This approach is not only relevant to the research question and key-concept data but also helps in proposing new avenues to expand the research in the field of educational technology (Tinto, 1975; Bean, 1988; Tight, 2019; Rowe *et al.*, 2022; Guarda *et al.*, 2023; Santos *et al.*, 2023).

3.8 Key-concept data

The key-concept data definitions and references provide a foundation for the literature review, each playing a distinct yet interconnected role in shaping the investigation (Donthu *et al.*, 2021). Table 2 presents these concepts and the purpose related to the search.

Table 2: Key concept data

Concepts	Definition	Purpose
Academic Achievement	Grade point average (Liu & Liu, 2000).	To measure the influence the intervention has on student grades.
Adaptive Learning Technology	Learning and teaching technology is designed to cater to individual student needs by tailoring content to their pace and understanding (Luckin et al., 2016) (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 (Luckin et al., 2016).	The focus is AI's role in peer-supported learning and teaching, examining its effects on achievement and engagement.
Dependent Variable	These variables are measured or observed to assess the impact of change in the independent variable of the conceptual framework. There are two dependent variables.	Determine the level of interaction caused by the AI peer-to-peer support among the students. It evaluates the students' performance based on their grades.
Engagement	Engagement in education refers to the level of interest, enthusiasm, and concern students have towards learning, with higher levels of engagement being typical goals set by educators (Glossary and Great Schools Partnership, 2016).	The study explores engagement dimensions in AI-based teaching, examining factors affecting student engagement and potential benefits for improved retention and performance.
Independent Variable	The variable whose change is purposely caused by observing its effect on other variables. The conceptual framework's independent variable is "AI Peer-to-Peer Support."	The effects of AI are being evaluated and analysed in terms of its existence and application in peer-to-peer support.
Peer-Support Technology	Peer learning tools include online forums, social networks, tutoring platforms, and collaborative software(Topping, 2005).	Explore the effectiveness of AI peer-to-peer support, focusing on students' engagement beliefs.
Personalised Learning (PL.)	Individualising learning tailors content and instruction methods (Han and Ellis, 2020).	Understanding the impact of AI platforms' customisation on academic success and student engagement is crucial.
Traditional 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.	The more basic is centred on academics and AI platforms to help students fit within and engage with.

Concepts	Definition	Purpose
A belief system framework includes two key components: Engagement and Support Systems.	The increased physical and mental activity among students regarding academic work and group study enhances their more profound understanding of learning and commitment to education (Schommer-Aikins, 2012).	The study examines the impact of AI on student engagement and the effectiveness of peer assistance.

The narrative explains the concepts and their purposes, providing a comprehensive understanding of the elements involved in the study.

- **Academic achievement:** The Grade Point Average (GPA) measures student outcomes or accomplishments (Liu & Liu, 2000).
- **Adaptive learning technology:** Customises content delivery to individual learning rates and competencies, enhancing understanding and mastery (Xiao *et al.*, 2020).
- **AI in learning and teaching:** Uses intelligent technologies for personali*s*ed tutoring, automating processes to increase efficiency and effectiveness (Luckin *et al.*, 2016; Shemshack & Spector, 2020).
- **Engagement:** Encompasses intellectual, emotional, behavioural, physical, and cultural aspects of students' motivation, cognition, and behaviour (Glossary and Great Schools Partnership, 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.
- **Peer-support technology:** Facilitates collaborative learning experiences through online forums, social networks, and tutoring platforms (Topping, 2005).
- **Personalised learning (PL):** Individualising the learning flow to personalise (individualisation) content and tailor tuitional methods (differentiation) (Han and Ellis, 2020). This individualisation involves individual students customising the learning program at a particular pace (individualisation), using a tailor-made instructional method (differentiation), and creating content for personalised learning.
- **Traditional peer support:** 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).
- **Retention:** Tinto (1975) argues that successful integration into the academic and social system and individual commitment to graduation and the institution yields positive outcomes.
- **Belief system framework:** Comprises the broader belief systems 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, the learning theories of personalisation, socio-economic, constructivism and humanism may be regarded as one of the main features of an AI peer-to-peer support system because these theories reflect the essence that determines the AI setting (Kember & Hicks, 2023). The area of interest is the use of AI for learning and teaching, as well as related areas like learning technology, peer-supportive technology and professional knowledge.

3.9 Databases and sources

Beyond primary literature, the search integrated conference proceedings, technical reports, preprints, and blogs. The analysis covered sixty-eight secondary data sources, comprising eight lecture notes, 28 articles, 20 conference papers, seven reviews, and five book chapters. Key-concept data is extracted from the literature using Mendeley's reference manager, downloaded into VosViewer mapping software, sorted into clusters and analysed.

Table 3 reports the accessed databases and their focus areas to ascertain the use of AI in peer-to-peer support within educational contexts.

Table 3: Primary Databases and Sources

Database/Source	Description	Focus
Google Scholar	Provides access to a wide array of peer-reviewed articles and theses.	General academic research across various disciplines.
Springer	Extensive collection of academic books, journals, and conference papers.	Science, technology, medicine, and education.
IEEE Explore	Contains technology-focused papers on AI applications.	Engineering, technology, and AI in education.
Research Gate	A social networking site for researchers to share papers and collaborate.	General academic research, networking, and collaboration.

This database and source strategy ensures that the selected literature provides insights into whether institutions harness AI platforms as peer-to-peer support.

4. Results

Previous research has explored AI separately in learning and teaching and the effect of traditional peer-to-peer techniques (Topping & Ehly, 1998; Sharma *et al.*, 2023). This study examines AI's use in peer-to-peer support within learning environments. "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).

4.1 Network visualisation and co-word analysis

The co-word analysis has revealed noteworthy developments through a hermeneutic approach of 1113 research publications on AI and learning (Boell & Cecez-Kecmanovic, 2014). These include the overall impact of AI on peer-to-peer support (Kolchenko, 2018; Taneri, 2020; Mota, 2023; Minn, 2022; Chan, 2023; Toksha *et al.*, 2022; Capuano & Caballé, 2020).

4.2 Themes and trends

In the network visualisations that follow, co-words appear with labels and, by default, a coloured circle representing a cluster. The size of the label and the circle depends on the number of coexistences of the words. Lines between clusters and co-words represent links. The heavier the coexistence, the bigger the label and the circle. The search for AI in peer-to-peer support finds less specific content, suggesting an underexplored area. The discourse seems to focus on AI's role and functions within general pedagogy, not peer support, as illustrated in Figure 3.

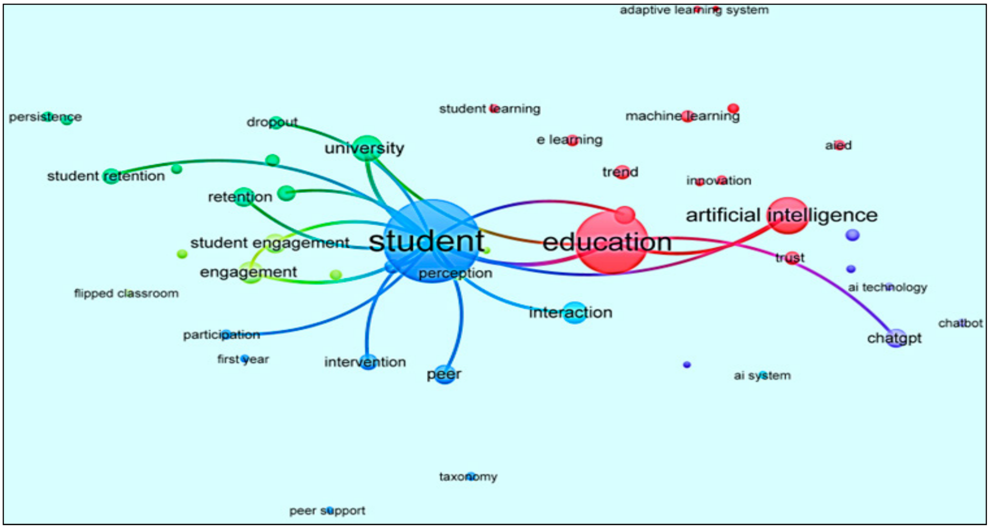

Figure 3: Co-Words and Terms 2020-2023

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".

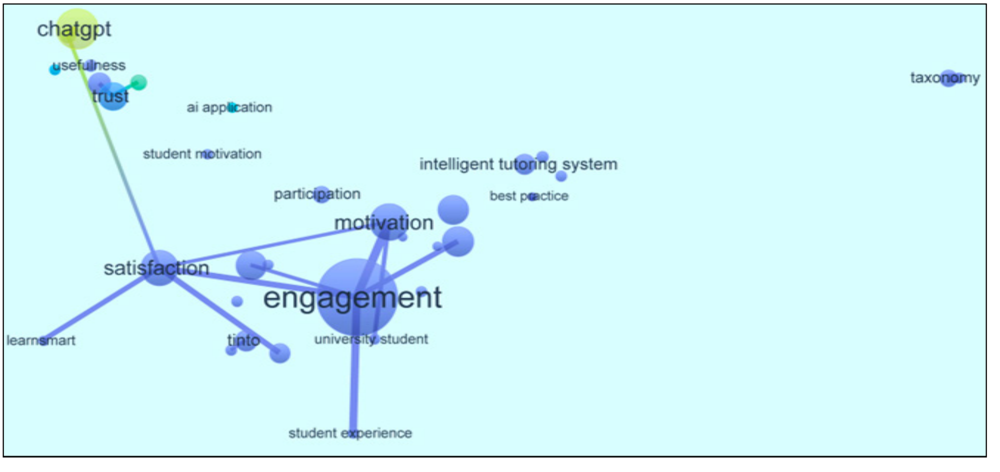

Figure 4 Links to ChatGPT 2020-2023

During 2023, a significant focus on ChatGPT was clear, with 16 keyword and term occurrences and a correlation coefficient 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, as illustrated in Figure 4.

Table 4: Summary of gap analysis

Concepts	Connection	Description	Relationship	Direct or Indirect Connection	Gap Description
Student and Education	Strong	The core of the network, indicating primary importance and high correlation	AI and Peer Support	Indirect	AI is connected to education through innovation and e-learning, while peer support correlates with engagement.
AI and Machine Learning	Moderate	Linked to education and student learning, relationships are weaker and more distant.	AI and Engagement	Indirect	AI connects to education, which links to interaction and engagement.
Peer Support and Engagement	Significant	Connected to students and education through intervention and interaction.	AI, Persistence and Retention	Indirect	AI links to student learning and education and then connects to retention and persistence.
Persistence and Retention	Strong	Connected and related to student retention, university, and engagement.	Peer Support and Retention	Indirect	Peer support connects to retention through engagement and intervention.

Table 4, Summary of the gap analysis, confirms notable indirect (weak) connections between AI and peer support, engagement, and retention concepts. AI's relationship with peer support is mediated through education, innovation, and e-learning, indicating a potential area for exploring AI's direct role in enhancing peer support mechanisms. Similarly, AI's connection to engagement is indirect (weak), suggesting opportunities to investigate how AI tools can more directly influence student engagement and peer support. Furthermore, the relationship between AI and persistence or retention is also indirect (weak), highlighting the need for research into AI applications that directly affect student retention and persistence. While significant, the link between peer support and retention is mediated through engagement and intervention, suggesting that strengthening peer support mechanisms could positively impact retention rates.

The analysis identifies gaps and opportunities for leveraging AI to enhance peer-to-peer support relationships and references, particularly fostering peer support and improving student retention and persistence.

5. Discussion and findings

The gap analysis highlights the indirect (weak) connections between AI, peer support, engagement, and retention, providing a foundation for integrating established retention and attrition theories into future research, as illustrated in Figure 5. The theories underscore the significance of social and academic integration, which AI can potentially enhance (Wentzel & Wigfield, 1998).

Gap Matrix Aligned to Theories-Tinto and Bean

Theories	Personalised	Socio-Emotional	Constructivist	Humanistic
Peer Support		Gap		
AI Learning			Gap	
AI System	Gap	Gap		
ChatGPT				Gap

Figure 5: Gap matrix aligned to theories

Researchers may assess the impact on student engagement and performance by developing AI tools that support peer interactions and personalised learning experiences.

Notably, there could be more association with AI applications, taxonomy, student motivation, participation, and peer-to-peer support. The absence of alignment between learning theories, student motivation as presented by Tinto (1975), taxonomy, intelligent tutoring system, participation, and best practice reveals a research gap, as shown in Figure 5. Integrating AI into peer tutoring raises intricate questions about its influence on students' beliefs with engagement, academic achievement, and learning platforms affecting retention.

While AI has effects on pedagogy, the direct impact of AI on peer-to-peer supported learning has not been well-researched. This lack of research means a dearth of knowledge on how AI can contribute to peer relationships and supportive structures and its effect on outcomes. The study answers the question: Does the literature show that AI facilitates peer-to-peer support?

5.1 Theoretical implications

The analysis shows that mediating variables link AI to important educational concepts like engagement, persistence, and retention. The relationship between AI and these areas is through enhancing peer learning, e-learning, and innovation.

5.2 Practical implications

The revived focus on ChatGPT proves that it can positively impact student satisfaction and engagement; however, further research requires its contribution to establishing AI peer-supported learning.

5.3 Research gaps in AI and peer support

This study's gap analysis shows how AI peer-to-peer support may be directly associated with traditional peer support; therefore, future studies should directly assess the relationship between AI and peer support, interaction, and retention. This bibliometric and hermeneutic analysis indicates that a design and methodology strategy is required to conduct a case study on the impact of AI on participation, peer support, and persistence.

6. Directions for future research

Future research should investigate AI peer-to-peer support's role in reducing attrition, improving retention, and personalising learning. Studies should also explore AI's impact on socio-emotional learning and its integration into constructivist and humanistic learning approaches.

6.1 Retention and attrition

Further research should investigate using AI peer-to-peer support to reduce attrition and improve retention rates. The implication of using AI peer-to-peer support is that it may prevent undesirable situations, providing needed assistance and tools to the students to avoid falling behind. Also, using AI-based platforms could create a learning community for the students since they are the primary users of the platforms and enhance the student's motivation and commitment to the educational programs.

6.2 Personalised learning

AI peer-to-peer support could personalise the learning experience by tailoring content to specific learners and learning rates, enhancing learners' interest and understanding. The goal should be to see how adaptive learning systems can provide real-time feedback and individual learning plans. These interventions could improve the learning results and help students become masters of their learning.

6.3 Socio-emotional learning

AI peer-to-peer support may help improve social relations through learning platforms that link students for group assignments, group discussions, and group tutoring. These platforms should help students find each other based on their skills and learning objectives. AI peer-to-peer support may provide instant feedback on course content, advising students on their performance and what must be corrected.

6.4 Constructivist and humanistic approaches

Two other potential research directions include general relationships between AI and the key ideas of the constructivist and humanistic paradigms of peer-to-peer support. Further investigations should touch upon the consequences of AI adoption in learning experiences, given the activities involving the student's learning needs for enhancing their critical thinking and critical thinking skills. AI peer-to-peer support could show real-life scenarios so the students can practice those essential thinking skills and make mistakes that don't have dire repercussions. In addition, it could revolutionise humanistic learning by ascertaining the learning capacity and the field of interest, creating a noble learning process that recognises each learner's potential. Future research could investigate how AI-driven personalised learning and support systems improve student satisfaction and academic outcomes.

7. Recommendations

A recommended follow-up study should adopt a mixed-methods approach to comprehensively explore the role of AI in facilitating peer-to-peer learning. This study should examine its effects on student retention, academic performance, and belief systems at a selected university in the Western Cape. The quantitative component should analyse[1] performance metrics and retention rates among students engaged in AI-supported peer learning. In contrast, the qualitative component should gather detailed insights through interviews, focus groups, and classroom observations. This design would address the limitations of bibliometric analysis by capturing the nuanced, real-world dynamics of AI integration in educational settings. It would provide a more holistic understanding of how AI shapes peer-to-peer learning experiences and outcomes, including the shifts in students' attitudes, perceptions, and learning behaviours over time. The following recommendations enrich AI's knowledge base as well as strengthen its existing practice in the promotion of peer-to-peer support for learning:

7.1 Identifying causal relationships

To establish causal relationships between AI peer-to-peer support and educational outcomes, researchers should employ rigorous methodologies such as:

- **Randomised controlled trials (RCTs):** Conduct experiments where participants are randomly assigned to AI-supported peer learning groups and control groups without AI support. This randomisation will help isolate the effect of AI interventions.
- **Longitudinal studies:** Track student performance, engagement, and retention over time to observe the long-term impact of AI peer-to-peer support.
- **Quasi-experimental designs:** Use natural experiments where random assignment is not possible. Methods like propensity score matching can help control for confounding variables.
- **Mixed methods approach:** Combine quantitative data (e.g., grades, retention rates) with qualitative insights (e.g., student interviews, focus groups) to provide a comprehensive understanding of AI's impact.

7.2 Measuring engagement and retention metrics

Accurate measurement of engagement and retention is crucial. Recommended metrics and tools include:

7.2.1 Engagement metrics

- **Behavioural indicators:** Attendance, participation in online discussions, and frequency of interactions with AI tools.
- **Emotional indicators:** Student satisfaction surveys and mood tracking via sentiment analysis of written feedback.
- **Cognitive indicators:** Time spent on tasks, number of completed assignments, and depth of online discussion posts.

1 Grammarly used to support the use of British English language.

7.2.2 Retention metrics

- **Retention rates:** Percentage of students who continue their studies from one year to the next.
- **Graduation rates:** Students' completion rates within a certain period.
- **Dropout rates:** Drop out of the students from the program before the completion of the program.

7.2.3 Tools

- **Learning management systems (LMS):** Tools such as Canvas, Moodle, or Blackboard allow monitoring of student participation's extent and dynamics.
- **Survey tools:** Researchers can use tools like the National Survey of Student Engagement (NSSE).
- **Data analytics software:** Engagement and retention data analysis is compiled using software like Tableau, SPSS, and R.

7.3 Cross-disciplinary studies

Researchers can examine AI's effects on peer-to-peer learning across multiple fields to ensure the general applicability of the findings. Disciplines and study design could be:

- **STEM** (science, technology, engineering, mathematics): Investigate AI's role in collaborative problem-solving and laboratory-based learning. Use case studies and experimental designs.
- **Humanities and social sciences:** Explore AI's support in discussion-based and project-based learning environments. Implement ethnographic studies and longitudinal designs.
- **Health sciences:** Assess AI's contribution to clinical simulations and peer mentoring in nursing and medical education. Use cohort studies and RCTs.
- **Business and management:** Examine AI's effectiveness in group projects and peer feedback mechanisms. Utilise mixed-methods research combining surveys and performance analytics.
- **Arts and design:** Evaluate AI's role in creative collaborations and peer critiques. Conduct action research and qualitative case studies.

7.4 Ethical considerations

The use of AI in education creates the following ethical concerns. Best practices to address these concerns include:

- **Privacy and data security:** All the data about the students collected by the AI systems should be encrypted and stored correctly.
- **Bias and fairness:** It is advisable to perform a recurrent assessment of AI algorithms for signs of prejudice that might affect some people. Ensure fairness checks are in place and include persons from different backgrounds in the development of AI.
- **Transparency and accountability:** Inform the students and educators of the AI systems' strengths and weaknesses—set guidelines and processes to hold individuals/organisations responsible for AI decisions.

- **Informed consent:** Seek permission from students to use their data for AI-driven interventions and tell them how their data will be utilised and protected.
- **Digital divide:** Eliminate disparities in AI tool availability by ensuring all students, especially those from marginalised backgrounds, are equipped with the needed materials.
- **Human oversight:** Enforce that the AI systems act as assistants to human judgment and not as a substitute for it. Ensure that there is always a balance whereby the lecturers can sometimes step in and correct or change the decision made by the AI.

8. Conclusion

This literature review aimed to explore the application of AI in peer-to-peer support in educational contexts by analysing 1113 academic records. Employing a four-phase exploratory design and an inductive, reflexive thematic approach, the study aimed to uncover whether AI enhances peer-to-peer learning and its subsequent impact on student outcomes and retention.

The findings reveal a significant gap in direct research focused on AI's role in peer-to-peer support. While previous studies have separately explored AI in learning, teaching, and traditional peer-to-peer methods, there is a notable lack of integration between these areas. The analysis indicates that AI has the potential to enhance personalised learning, socio-emotional engagement, constructivist participation, and humanistic growth, all of which are critical to improving academic performance and retention rates.

Despite the indirect (weak) connections identified between AI and vital educational outcomes such as engagement, persistence, and retention, the study underscores the potential of AI tools to foster student satisfaction and innovative learning experiences. However, the need for empirical research to establish causal relationships and directly assess AI's effectiveness in peer-to-peer learning contexts remains paramount.

Future research should focus on developing and evaluating AI-driven interventions to reduce student attrition, enhance personalised and socio-emotional learning, and foster constructivist and humanistic educational approaches. Additionally, cross-disciplinary studies and ethical considerations will be essential to ensure AI technologies' broad applicability and fairness in diverse academic settings.

In conclusion, while AI shows promise as a facilitator of peer-to-peer support, further research is necessary to fully understand and harness its potential to improve student outcomes and retention in higher education. The findings of this study provide a foundational framework for future investigations and practical applications in educational technology.

References

Alonso-Muñoz, S., Torrejón-Ramos, M., Medina-Salgado, M.-S. & González Sánchez, R., 2023. Trends in Mentoring at Higher Education: A bibliometric analysis. In the proceedings book: International conference on innovation, documentation and education. INNODOCT/22. Valencia, November 2nd-7th 2022. https://doi.org/10.4995/INN2022.2023.15704

Balilah, M., Babgi, M., Alnemari, W., Binjabi, A., Zaini, R., Abdulkhaliq, A., Monjed, A., Aldahlawi, S. & Almoallim, H., 2020. A proposed framework to develop, describe and evaluate peer-assisted learning programs. *Advances in Medical Education and Practice*, 1005–1013. https://doi.org/10.2147/AMEP.S282582

Bean, J.P., 1980. Dropouts and turnover: The synthesis and test of a causal model of student attrition. *Research in Higher Education*, 12(2): 155–187. https://doi.org/10.1007/BF00976194

Bean, J.P., 1988. Leaving college: Rethinking the causes and cures of student attrition. The Journal of Higher Education, 59(6):708–711. https://doi.org/10.1080/00221546.1988.11780239

Bean, J.P. & Metzner, B.S., 1985. A conceptual model of nontraditional undergraduate student attrition. *Review of Educational Research*, 55(4):485–540. https://doi.org/10.3102/00346543055004485

Boell, S.K. & Cecez-Kecmanovic, D., 2014. A hermeneutic approach for conducting literature reviews and literature searches. *Communications of the Association for Information Systems*, 34(1), 12. https://doi.org/10.17705/1CAIS.03412

Bork, A.M., 1999. The Future of Learning: An Interview with Alfred Bork. *Educom Review*, 1–4. https://library.educause.edu/resources/1999/1/the-future-of-learning-an-interview-with-alfred-bork

Braun, V. & Clarke, V., 2019. Reflecting on reflexive thematic analysis. *Qualitative Research in Sport, Exercise and Health*, 11(4):589–597. https://doi.org/10.1080/2159676X.2019.1628806

Capuano, N. & Caballé, S., 2020. Adaptive learning technologies. *AI Magazine*, 41(2):96–98. https://doi.org/10.1609/aimag.v41i2.5317

Carini, R.M., Kuh, G.D. & Klein, S.P., 2006. Student engagement and student learning: Testing the linkages. *Research in Higher Education*, 47(1). https://doi.org/10.1007/s11162-005-8150-9

Chan, C.K.Y., 2023. A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Educatio*n 20(38). https://doi.org/10.1186/s41239-023-00408-3

Chang, Y.-W., Huang, M.-H. & Lin, C.-W., 2015. Evolution of research subjects in library and information science based on keyword, bibliographical coupling, and co-citation analyses. *Scientometrics*, 105(3): 2071–2087. https://doi.org/10.1007/s11192-015-1762-8.

Chapman, D., 2011. Learning management systems. In: *Encyclopedia of Distance Learning*. https://doi.org/10.4018/978-1-59140-555-9.ch182

Cui, T. & Wang, J., 2024. Empowering active learning: A social annotation tool for improving student engagement. *British Journal of Educational Technology*, 55(2). https://doi.org/10.1111/bjet.13403

Davidson, J.C. & Wilson, K.B., 2017. Community college student dropouts from higher education: Toward a comprehensive conceptual model. *Community College Journal of Research and Practice*, 41(8): 517–530. https://doi.org/10.1080/10668926.2016.1206490

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N. & Lim, W.M., 2021. How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, 133: 285-296. https://doi.org/https://doi.org/10.1016/j.jbusres.2021.04.070

Eisner, E.W., 2017. *The enlightened eye: Qualitative inquiry and the enhancement of educational practice*. New York: Teachers College Press.

Etzkorn, K.B. & Braddock, A., 2020. Are you my mentor? A study of faculty mentoring relationships in US higher education and the implications for tenure. *International Journal of Mentoring and Coaching in Education*, 9(3): 221–237. https://doi.org/10.1108/IJMCE-08-2019-0083

Fokkens-Bruinsma, M., Vermue, C., Deinum, J.F. & van Rooij, E., 2021. First-year academic achievement: the role of academic self-efficacy, self-regulated learning and beyond classroom engagement. *Assessment and Evaluation in Higher Education*, 46(7). https://doi.org/10.1080/02602938.2020.1845606

Glossary and Great Schools Partnership, 2016. *Student Engagement*. The Glossary of Education Reform. https://www.greatschoolspartnership.org/resources/glossary-of-education-reform/

Goldoni, D., Reis, H.M., Carrascoso, M.M. & Jaques, P.A., 2023. Computational tools to teach and develop socio-emotional skills: A systematic mapping. *International Journal of Learning Technology*, 18(2). https://doi.org/10.1504/IJLT.2023.132758

Guarda, T., Barrionuevo, O., Victor, J.A. (2023). Higher Education Students Dropout Prediction. In: Rocha, Á., Fajardo-Toro, C.H., Riola, J.M. (eds) Developments and Advances in Defense and Security. Smart Innovation, Systems and Technologies, 328. Springer, Singapore. https://doi.org/10.1007/978-981-19-7689-6_11

Halverson, L.R. & Graham, C.R., 2019. Learner engagement in blended learning environments: A conceptual framework. *Online Learning*, 23(2):145–178. https://doi.org/10.24059/olj.v23i2.1481

Han, F. & Ellis, R., 2020. Personalised learning networks in the university blended learning. *Comunicar*, 28(62). https://doi.org/10.3916/C62-2020-02

Kelly, S., Kaye, S.-A. & Oviedo-Trespalacios, O., 2023. What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, 77, https://doi.org/10.1016/j.tele.2022.101925

Kember, D., Hicks, D. (2023). Modelling the way teachers can support the retention and success of online students. In: D. Kember, R.A. Ellis, S. Fan, A. Trimble, A. (Eds) *Adapting to Online and Blended Learning in Higher Education*. Springer, Singapore. https://doi.org/10.1007/978-981-99-0898-1_14

Kolchenko, V., 2018. Can modern AI replace teachers? Not so fast! Artificial intelligence and adaptive learning: Personalised education in the AI age. *HAPS Educator*, 22(3):249–252. https://files.eric.ed.gov/fulltext/EJ1227770.pdf. https://doi.org/10.21692/haps.2018.032

Li, L., Zhao, T., Xie, Y., Feng, Y. (2020). Interpretable machine learning based on integration of NLP and psychology in peer-to-peer lending risk evaluation. In: X. Zhu, M. Zhang, Y. Hong, R. He, (Eds). *Natural Language Processing and Chinese Computing. NLPCC 2020. Lecture Notes in Computer Science*, 12431. Springer, Cham. https://doi.org/10.1007/978-3-030-60457-8_35

Liu, R. & Liu, E., 2000. Institutional integration: An analysis of Tinto's theory. https://files.eric.ed.gov/fulltext/ED445629.pdf

Luckin, R., Holmes, W., Griffiths, M. & Forcier, L.B., 2016. Intelligence unleashed: An argument for AI in education. *Open Research Online*. https://oro.open.ac.uk/50104/

Marco-Fondevila, M., Rueda-Tomás, M. & Latorre-Martínez, M.P., 2022. Active participation and interaction, key performance factors of face-to-face learning. *Education Sciences*, 12(7). https://doi.org/10.3390/educsci12070429

Minn, S., 2022. AI-assisted knowledge assessment techniques for adaptive learning environments. *Computers and Education: Artificial Intelligence*, 3, https://doi.org/10.1016/j.caeai.2022.100050

Mota, D. & Martins, C. (2023). AI in emergency remote learning environments: intelligent tutoring systems perspective. In S. Silva, P. Peres, & C. Silva (Eds.), *Developing Curriculum for Emergency Remote Learning Environments* (pp. 121-140). IGI Global Scientific Publishing. https://doi.org/10.4018/978-1-6684-6071-9.ch007

Pham, M.T., Rajić, A., Greig, J.D., Sargeant, J.M., Papadopoulos, A. & Mcewen, SA, 2014. A scoping review of scoping reviews: Advancing the approach and enhancing the consistency. *Research Synthesis Methods*, 5(4). https://doi.org/10.1002/jrsm.1123

Dos Reis, K.M. & Yu, D., 2018. Peer mentoring: Enhancing economics first years' academic performance. *South African Journal of Higher Education*, 32(6): 234–250. https://doi.org/10.20853/32-6-2979

Roscoe, R.D. & Chi, M.T.H., 2007. Understanding tutor learning: Knowledge-building and knowledge-telling in peer tutors' explanations and questions. *Review of Educational Research*, 77(4). https://doi.org/10.3102/0034654307309920

Rowe, M., Nicholls, D.A. & Shaw, J., 2022. How to replace a physiotherapist: Artificial intelligence and the redistribution of expertise. *Physiotherapy Theory and Practice*, 38(13): 2275–2283. https://doi.org/10.1080/09593985.2021.1934924

Rufii, R., 2015. Developing module on constructivist learning strategies to promote students' independence and performance. *International Journal of Education*, 7(1). https://doi.org/10.5296/ije.v7i1.6675

Santos, N.N., Pipa, J. & Monteiro, V., 2023. Analysing grade retention beliefs within teachers' psycho-pedagogic beliefs system. *Teaching and Teacher Education*, 121, p.103939. https://doi.org/10.1016/j.tate.2022.103939

Schommer-Aikins, M., 2012. An evolving theoretical framework for an epistemological belief system. In: B. K. Hofer, & P.R. Pintrich, (Eds.). (2002). Personal Epistemology: The Psychology of Beliefs About Knowledge and Knowing (1st ed.). Routledge. pp.103–118. https://doi.org/10.4324/9780203424964

Sharma, A., Lin, I.W., Miner, A.S., Atkins, D.C. & Althoff, T., 2023. Human–AI collaboration enables more empathic conversations in text-based peer-to-peer mental health support. *Nature Machine Intelligence*, 5(1): 46–57. https://doi.org/10.1038/s42256-022-00593-2

Shemshack, A. & Spector, J.M., 2020. A systematic literature review of personalised learning terms. *Smart Learning Environments*, 7(1):33. https://doi.org/10.1186/s40561-020-00140-9

Sormunen, K., Juuti, K. & Lavonen, J., 2020. Maker-centered project-based learning in inclusive classes: Supporting students' active participation with teacher-directed reflective discussions. *International Journal of Science and Mathematics Education*, 18(4). https://doi.org/10.1007/s10763-019-09998-9

Taneri, G.U., 2020. Artificial intelligence & higher education: Towards customised teaching and learning, and skills for an AI world of work. Research & Occasional Paper Series: *Center for Studies in Higher Education*. https://cshe.berkeley.edu/publications/artificial-intelligence-higher-education-towards-customized-teaching-and-learning-and

Tight, M., 2019. Student retention and engagement in higher education. *Journal of Further and Higher Education*, [online] 44(5): 689–704. https://doi.org/10.1080/0309877X.2019.1576860

Tinto, V., 1975. Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research*, 45(1): 89–125. https://doi.org/10.3102/00346543045001089

Toksha, B., Kulkarni, T. & Gupta, P., 2022. Impact of AI on teaching pedagogy and its integration for enhancing teaching-learning. In: P. Churi, S. Joshi, M. Elhoseny, & A. Omrane, (Eds.). *Artificial Intelligence in Higher Education: A Practical Approach* (1st ed.). CRC Press. pp.137–152. https://doi.org/10.1201/9781003184157

Topping, K. & Ehly, S., 1998. *Peer-assisted learning*. Routledge. https://doi.org/10.4324/9781410603678

Topping, K.J., 2005. Trends in peer learning. *Educational Psychology*, 25(6): 631–645. https://doi.org/10.1080/01443410500345172

Wentzel, K.R. & Wigfield, A., 1998. Academic and social motivational influences on students' academic performance. *Educational Psychology Review*, 10, 155–175: https://doi.org/10.1023/A:1022137619834

Xia, Q., Chiu, T.K.F., Zhou, X., Chai, C.S. & Cheng, M., 2022. Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, 4: p.100118. https://doi.org/10.1016/j.caeai.2022.100118

Xiao, J., Wang, L., Zhao, J. & Fu, A., 2020. Research on adaptive learning prediction based on XAPI. *International Journal of Information and Education Technology*, 10(9): 679–684. https://doi.org/10.18178/ijiet.2020.10.9.1443

Zhao, W., Liu, X., Shah, S., Baah, I., Patel, A. & Wise, N., 2021. Peer support in smart learning and education. *2021 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/IOP/SCI)*, 18-21 October 2021, Atlanta, GA, USA, 2021, pp. 598-605, https://doi.org/10.1109/SWC50871.2021.00089