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PAPER

Mobile-Optimized AI-Driven Personalized Learning: A Case Study at Mohammed VI Polytechnic University

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ABSTRACT

With the rise of mobile learning platforms, it has become increasingly evident that individuals require personalized experiences that are tailored to the strengths and limitations of mobile devices. The present study explores the significant impact that personalized mobile learning environments, powered by artificial intelligence (AI), could have. This study specifically evaluates the impact of an AI-driven personalized educational platform, designed for mobile devices, on the academic achievement and educational progress of students at Mohammed VI Polytechnic University. The platform, designed for mobile devices, allows instructors to easily upload information. Learners can interact with an AI mentor through a chat interface that is seamlessly integrated into their mobile course materials. The system, constructed using cutting-edge technologies such as Langchain, Pinecone, and the LLM Model, excels at providing personalized, real-time feedback and support for learners who are frequently mobile. This study compared two groups of students. One group had access to a mobile personalized learning platform powered by AI, whereas the control group did not have access to it. We conducted a comparative analysis of mobile educational experiences, levels of engagement, and academic outcomes across these groups. In addition, qualitative feedback was gathered from educators and students to evaluate the mobile usability and effectiveness of the system. The results of our study demonstrate that the AI-driven mobile-tailored learning system significantly improves the experience of mobile learners. The increased levels of engagement, improved understanding, and superior academic achievements support our claim. This study not only supports the potential of AI-driven personalized mobile learning in higher education but also emphasizes the importance of continuous innovation to improve its usefulness and effectiveness.

KEYWORDS

personalized learning, mobile learning, artificial intelligence (AI), AI in education, intelligent tutoring systems (ITS), learner engagement

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1 INTRODUCTION

Significant transformation is evident, as there is a shift away from conventional, uniform teaching methods towards more customized and adaptable approaches [1]. The concept of personalized learning acknowledges the diverse requirements, competencies, and learning styles of learners and aims to tailor educational experiences accordingly [2]. According to [3], the fundamental concept of personalized learning is to provide learners with customized instruction, feedback, and support, thereby helping them reach their full potential and improve their academic achievements.

1.1 Overview of artificial intelligence-driven personalized learning systems

The significance of personalized learning in the field of education can be attributed to various factors. The initial point of discussion pertains to accommodating a diverse population of students with distinct learning preferences, cognitive aptitudes, and prior knowledge [4]. Through customizing the learning process, educators can effectively provide students with personalized support and resources that meet their individual needs [5]. Research has shown that this specific method enhances engagement and motivation among learners, as they feel a stronger connection to the subject matter and a sense of ownership over their educational development [6].

Personalized learning fosters a learner-centric approach to education, enabling students to take responsibility for their learning and develop essential skills such as self-regulation, critical thinking, and problem-solving [7]. The focus on active learning and metacognition, supported by collaborative experiential learning methods, aims to equip students with the essential skills to succeed in a rapidly evolving world driven by technological advancements [8] [9].

The emergence of digital technologies and data-driven analytics has facilitated the development of advanced personalized learning systems [10]. The systems mentioned above use artificial intelligence (AI) and machine learning algorithms to analyze large amounts of student data, providing instant feedback and adaptively adjusting the learning path based on individual progress [11]. The integration of AI in the field of education has accelerated the adoption of personalized learning, offering flexible options that have the potential to revolutionize the approach to teaching and learning [12] [13].

1.2 Objective and research questions

The present study aims to investigate the impact of an AI-based personalized learning platform on the academic performance and learning experience of students at Mohammed VI Polytechnic University. The system being considered facilitates the process of teachers uploading course materials and allows students to interact with an intelligent tutor through a chat interface integrated within the course documents. The system utilizes advanced technologies such as Langchain, Pinecone, and the LLM Model to provide customized and instant feedback and assistance. Through an assessment of the effectiveness of this innovative methodology, our goal is to make a valuable contribution to the growing body of literature on personalized instruction and its potential implications for the future of teaching.

2 LITERATURE REVIEW

The rapid advancements in the field of AI have enabled the development of various methods for personalizing education. The methods have been specifically developed to enhance the process of acquiring knowledge by providing personalized feedback, adaptable learning paths, and customized materials that are tailored to the diverse needs and preferences of learners [11]. Scholars have explored different personalization techniques that leverage AI, including intelligent tutoring systems (ITS), adaptive learning platforms, and recommendation systems [14] [15] [16]. Research has shown that integrating AI into personalized learning can lead to significant improvements in learning outcomes, learner engagement, and satisfaction [12] [6].

2.1 The role of intelligent tutoring systems and chat interfaces

Intelligent tutoring systems have been recognized as a highly effective approach for implementing personalized learning [14]. The aforementioned systems utilize AI methods to provide customized guidance, assessment, and support by adapting to the learner's needs and progress [17]. According to VanLehn's research, the implementation of ITSs has been found to enhance educational achievement by providing personalized, real-time feedback and guidance to learners [18].

Chat interfaces have become increasingly prominent in the realm of personalized learning due to their ability to facilitate seamless interaction between learners and intelligent tutors, as well as ITS [19]. The interfaces facilitate students' ability to engage in natural language dialogues with their instructors, replicating a personalized interaction with a human educator [20]. Chat interfaces have been found to enhance the personalized learning experience by allowing learners to ask questions and receive targeted support tailored to their individual concerns and misunderstandings [19] [21].

2.2 Technologies used in AI-based personalized learning (Langchain, Pinecone, and LLM model)

The integration of state-of-the-art AI technologies into personalized learning systems has led to more sophisticated and effective solutions. The LangChain framework is an advanced tool designed to simplify the development of language model-driven applications. The underlying assumption is that the most impactful and unique use cases will extend beyond basic interaction with a language model via an application programming interface (API). Instead, they will demonstrate two essential competencies: having an awareness of data and being proactive.

The concept of being data-aware refers to the ability of applications to effectively integrate and interact with various data sources. The mentioned capability allows the language models to use additional data, which creates a more comprehensive framework and enables more advanced responses.

The term "agentic" refers to the ability of language models to actively engage in interactions with their surroundings. The nature of this interaction can manifest in various ways, including environmental modification, decision-making based on environmental factors, and the acquisition of knowledge from these interactions to shape future responses.

In summary, LangChain is an innovative framework that enhances the capabilities of language model-driven applications by giving those data awareness and agency, ultimately optimizing their effectiveness and utility.

According to [22], the vector search engine enables the efficient and accurate retrieval of relevant information based on user queries and preferences. According to [23], the LLM Model, which is a large-scale language model, has the ability to generate text that is similar to human language and understand complex language structures. As a result, it is well-suited for providing personalized guidance and support.

According to [12], integrating various technologies into personalized learning systems has the potential to enhance their efficiency, adaptability, and ability to accommodate a broader audience, leading to more precise and context-specific personalization. According to [16], the adoption of a hybrid recommendation strategy, which is grounded in the recognition of learning styles, led to a notable enhancement in the customization of e-learning content. This enhancement resulted in higher learner satisfaction and performance.

3 METHODOLOGY

The present study uses a quasi-experimental research design, in which two distinct groups of students from the same class are compared. The experimental group has access to an AI-powered personalized learning system called Campus+, while the control group does not have access to the same system. This specific design enables the assessment of the impact of Campus+ on various factors, including student engagement, motivation, academic performance, and retention of course material.

The methodology used in this investigation is outlined below:

- **Pre-Implementation Phase:** During the pre-implementation phase of Campus+, a pre-test is conducted on both the experimental and control groups to assess their initial comprehension and retention of course materials. This provides a basic measure of students' academic achievement.
- **Implementation Phase:** During the implementation phase, the experimental group will have access to Campus+ for four weeks. At this stage, learners have the opportunity to engage with an AI-powered platform, ask questions, and receive personalized guidance and support. In the meantime, the observed group continues their academic pursuits without Campus+ intervention.
- **Post-Implementation Phase:** Following the implementation phase, a post-test is conducted on both groups during the post-implementation phase. The current assessment has been designed to measure the level of understanding, knowledge retention, and academic accomplishments of students who have used Campus+.

3.1 Participants and setting

In this study, a questionnaire survey is used to collect data. [24] suggests that sample sizes ranging from 40 to 500 are suitable for most research. Consequently, we have decided to use random probability sampling for this research. This procedure ensures a representative sample of students from the undergraduate computer science and medical sciences programs at Mohammed VI Polytechnic University.

The objective of the investigation is to assess and compare two groups of students from the same class. The first group will use the Campus+ AI-powered personalized educational platform, while the second group will not use this system. Upon completing the experimental phase, an evaluation will be conducted on both groups through a survey, focusing on their ability to retain and recall course content as well as other academic performance metrics.

The study involved undergraduate students from Mohammed VI Polytechnic University who were enrolled in four distinct academic disciplines: thermodynamics, operational research, neuroanatomy, and embryology. Out of the entire sample population, 46 individuals identified as male, constituting 45.5% of the total, while 55 individuals identified as female, making up 54.5% of the total. The participants were divided into two age categories: 18–20 years, with 26 individuals in the experimental group and 25 individuals in the control group, and 21–23 years, with an equal distribution of 25 individuals in both groups.

When analyzing the level of engagement with the Campus+ platform, it was discovered that 70.3% (n = 71) of users were categorized as active users, while 29.7% (n = 30) exhibited lower levels of involvement. Further investigation of the experimental group that used the Campus+ AI-driven personalized learning platform revealed that 76.5% (n = 39) of participants were actively engaged, while the remaining 23.5% (n = 12) were classified as inactive. In contrast, the control group using the conventional Campus+ platform had 66% active users (n = 33), while the remaining 34% (n = 17) were classified as inactive. Table 1 presents a comprehensive demographic breakdown.

Table 1. Demographic information of participants

Participant Characteristics	Experimental Group (Campus+ with AI)	Control Group
Total Participants	51	50
Age		
18–20	26	25
21–23	25	25
Gender		
– Male	23	23
– Female	28	27
Course		
– Thermodynamics	8	8
– Operational Research	11	11
– Neuroanatomy	11	11
– Embryology	9	10
Campus+ Usage		
– Active Users	39 (76%)	33 (66%)
– Inactive Users	12 (24%)	17 (34%)

3.2 Description of the AI-driven personalized learning system at Mohammed VI Polytechnic University

Mohammed VI Polytechnic University utilizes Campus+, an AI-powered personalized learning system. The mobile app was created to enhance students' educational experience and academic routine. It encompasses a variety of functions related to university life. The following section describes the fundamentals of Campus+. Campus+ keeps students informed about important campus news and developments. The software provides students with timely updates tailored to their preferences, academic interests, and extracurricular activities, enabling them to utilize the school's social network. The platform makes event management and connections with students, staff, and alumni easier. Campus+ simplifies student schedule management and university networking.

Campus+ offers user-friendly school management features that enable students to access course schedules and assignments and stay organized. This enhances the learning experience by helping students complete their assignments. Campus+ gamifies the academic experience by encouraging students to complete tasks, earn points, and achieve success. Gamification encourages academic, extracurricular, and social involvement. Campus+'s interior navigation system assists students in navigating the campus. This feature assists students in navigating the university's buildings and facilities, ensuring that they arrive on time for classes.

The core feature set of Campus+ revolves around its AI-based customization capabilities. The application customizes educational content to align with the unique needs and preferences of each student, optimizing their university experience. The Campus+ platform utilizes state-of-the-art AI tools, including Langchain, Pinecone, and the LLM Model, to provide instant assistance and evaluation to learners as they engage with academic content. The adoption of a personalized approach has been shown to enhance engagement, motivation, and academic results.

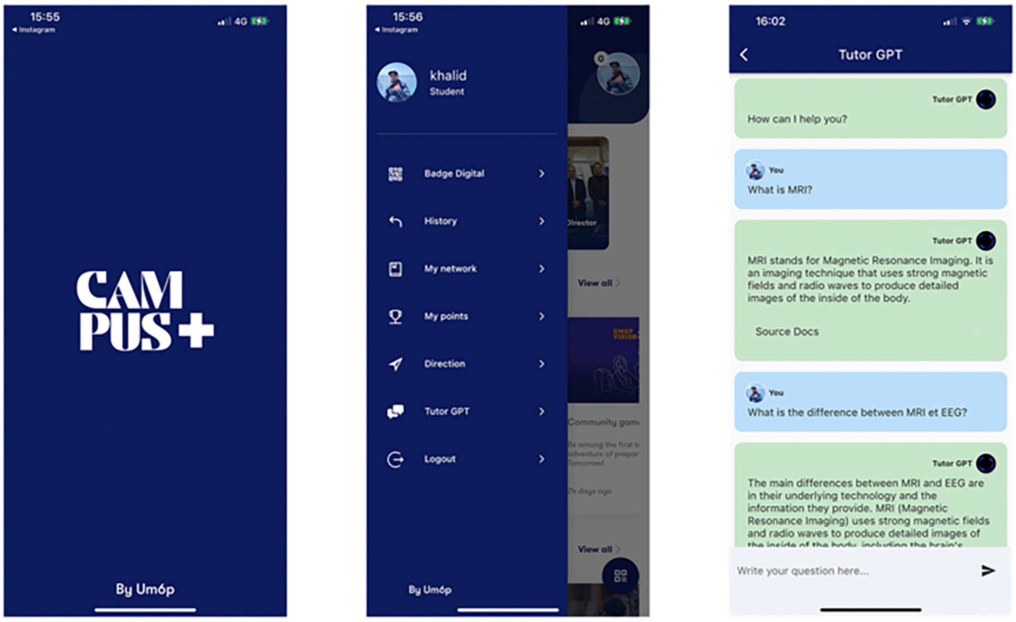

Fig. 1. Tutor GPT: A snapshot of the Campus+ application in action

In summary, Campus+ is an innovative personalized learning system that uses AI to integrate various features designed to enhance various aspects of the university experience at Mohammed VI Polytechnic University. Campus+ aims to establish a personalized and engaging learning environment that meets the diverse needs and preferences of the student population through the provision of customized educational content and the utilization of advanced AI technologies.

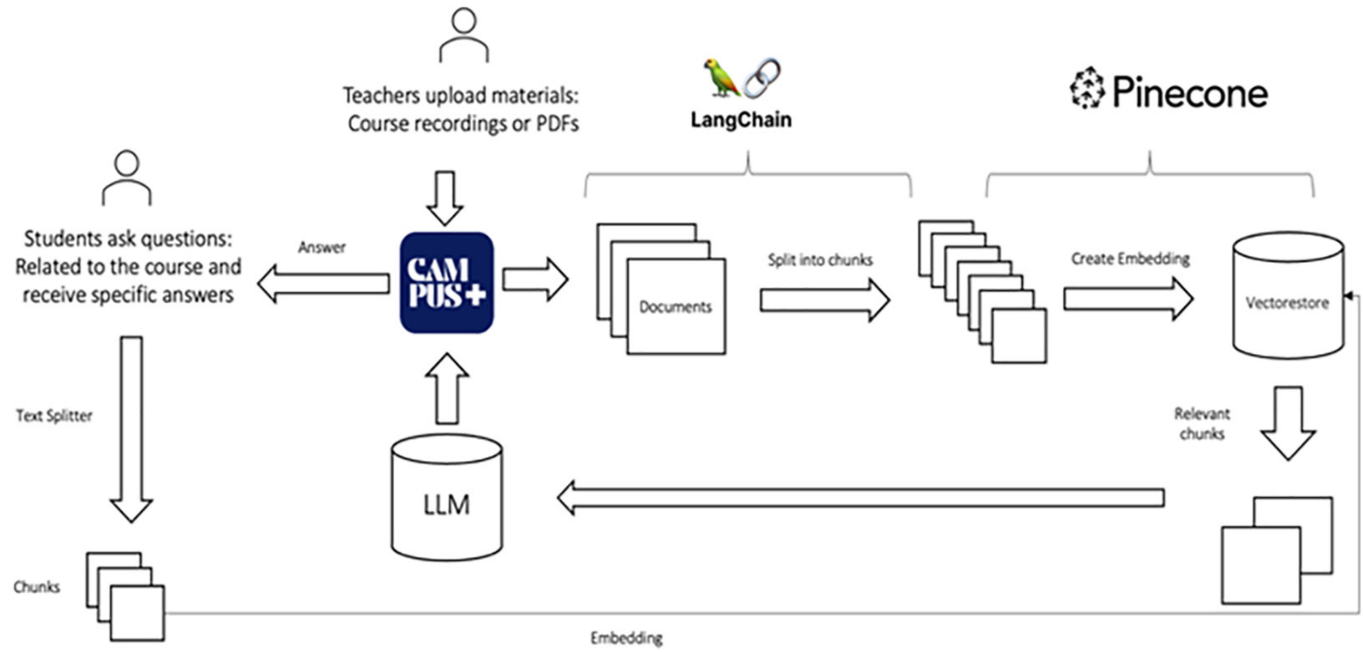

Fig. 2. AI-based personalized learning

Figure 2 illustrates the progression of a system designed to answer questions based on documents. This system integrates LangChain and Pinecone to effectively harness the capabilities of large language models (LLMs), such as OpenAI GPT-4. This system offers several advantages compared to the process of fine-tuning GPT models. It utilizes a tech stack that includes LangChain, Pinecone, Typescript, OpenAI, and Next.js. The LangChain framework facilitates the development of scalable AI and LLM applications and chatbots, thereby enhancing the system's capability to handle complex tasks. Pinecone is a vector repository that enables the storage of embeddings and textual data extracted from PDFs. It enables the quick retrieval of similar documents. The incorporation of this combination, along with semantic search and GPT Q&A, results in expanded knowledge coverage, contextually appropriate responses, increased flexibility, and improved handling of ambiguous queries.

The LangChain framework, as illustrated in the diagram, is a comprehensive system that offers a variety of modules to assist in the development of language model-driven applications. The modules provided are designed to address various aspects of the development process, including models, indexes, and chains. This facilitates a seamless integration of language models with semantic search and other related features.

The utilization of various techniques for generating word embeddings, which are essential for understanding and interpreting textual content, has significantly progressed in the field of AI in education in recent years. Word2Vec [25] is a method that captures semantic associations between words based on their proximity in a text corpus. It has two architectures: CBOW and Skip-gram. Negative sampling [25] and sub-sampling [26] are two alternatives that researchers have investigated to address issues such as sparse weight updates and computationally expensive softmax calculations. These methods enhance model accuracy and speed by tackling the issue of frequent word occurrences and optimizing weight updates. The study will utilize the GloVe model [27], which is a hybrid approach that effectively captures both local context information and global co-occurrence statistics of words. It combines the strengths of both window-based and count-based methods. The quality of word embeddings has significantly improved as a result of these techniques. However, further study is still needed to develop models that can effectively represent the nuanced connections and variations between words.

4 RESULTS

The data reveals that Campus+ was used by students of the thermodynamics (22%), operational research (30%), neuroanatomy (30%), and embryology (19%) programs. The integrated collaboration of multiple disciplines, particularly between operational research and neuroanatomy, is important as it allows for a more comprehensive and diverse analysis of learning events and their outcomes. The participation rates in thermodynamics and embryology classes were slightly lower than in other courses, but this does not invalidate the study's findings. Instead, it underscores the need for further research to fully understand these specific academic subjects.

An analysis of the data, as shown in Table 2, revealed significant differences between the pre-test and post-test scores of the two groups: control and experimental, across four academic disciplines: thermodynamics, operational research, neuroanatomy, and embryology. In thermodynamics, the average scores of the control group exhibited a slight increase, from 14.4 to 14.575. Conversely, the experimental group observed a significant increase, with scores rising from 14.3375 to 15.0375.

A similar pattern was observed in operational research: the mean scores of the experimental group increased from 14.12 to 14.74, while the control group saw a slight rise from 14.68 to 14.81. In the field of neuroanatomy, the mean scores of the control group increased from 14.65 to 14.84, while the experimental group experienced a more significant increase, rising from 14.27 to 14.93. In the subject of embryology, both groups showed improvement; however, the experimental group's increase from 15.67 to 16.22 was more significant compared to the control group's rise from 14.74 to 14.91.

Table 2. Comparative analysis of pre-test and post-test scores: Evaluating the efficacy of Campus+ across different subjects

Sub.	Grp.	Pre-TSM	Post-TSM	M. Diff.	SD Diff.	t-Val.	df.	p-Val.
Thermo.	C.	14,40	14,58	0.175	0.25	2.80	7	0.024
	E.	14,34	15,04	0.7	0.48	5.83	7	< 0.001
O. Research	C.	14,68	14,81	0.13	0.24	2.17	9	0.057
	E.	14,12	14,74	0.62	0.45	5.49	9	< 0.001
Neuroanatomy	C.	14,66	14,84	0.187	0.26	2.87	10	0.015
	E.	14,27	14,94	0.665	0.44	6.02	10	< 0.001
Embryology	C.	14,74	14,91	0.167	0.23	2.89	8	0.020
	E.	15,67	16,22	0.55	0.42	5.24	8	< 0.001

These findings indicate a general increase in post-test scores for both groups across all subject areas. Notably, the experimental groups consistently demonstrated a higher rate of improvement compared to the control groups, indicating that the experimental intervention used in this study may be effective. It is important to emphasize that these findings are preliminary, and further statistical investigations are necessary to determine the statistical significance of the observed differences [28].

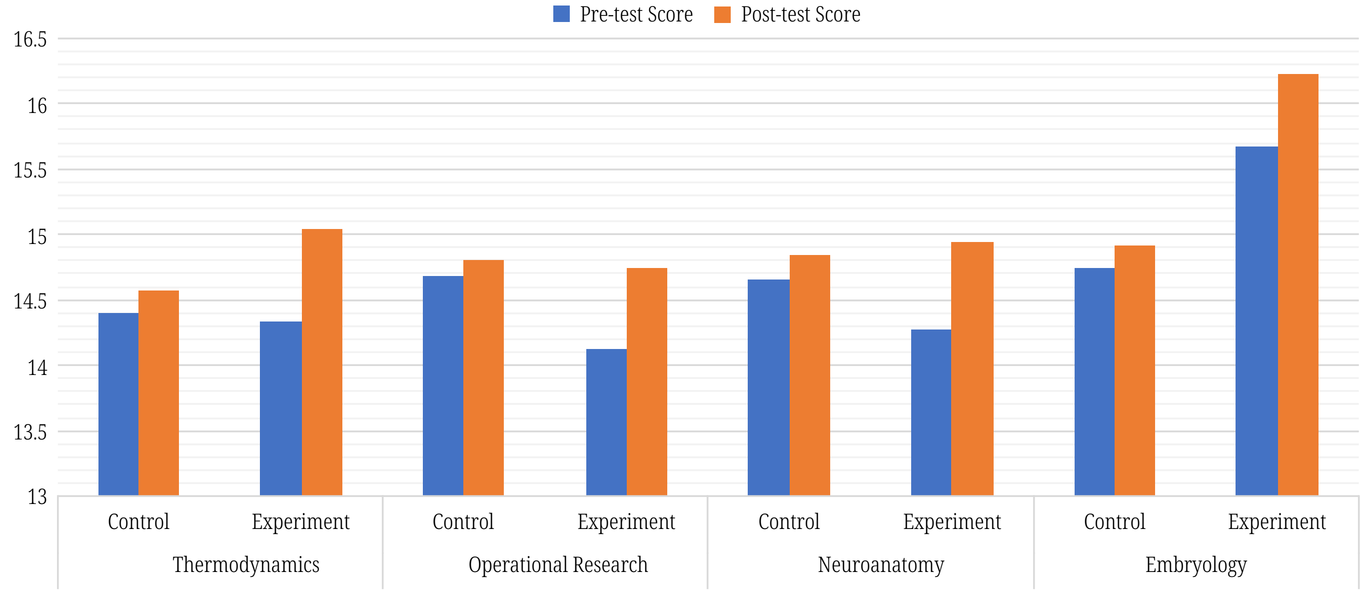

Fig. 3. Comparative analysis of pre-test and post-test scores across different academic disciplines and study groups

84% of students reported that Campus+ is "moderately effective" or "highly effective" in improving their learning efficiency, highlighting the tool's significance in enhancing academic understanding.

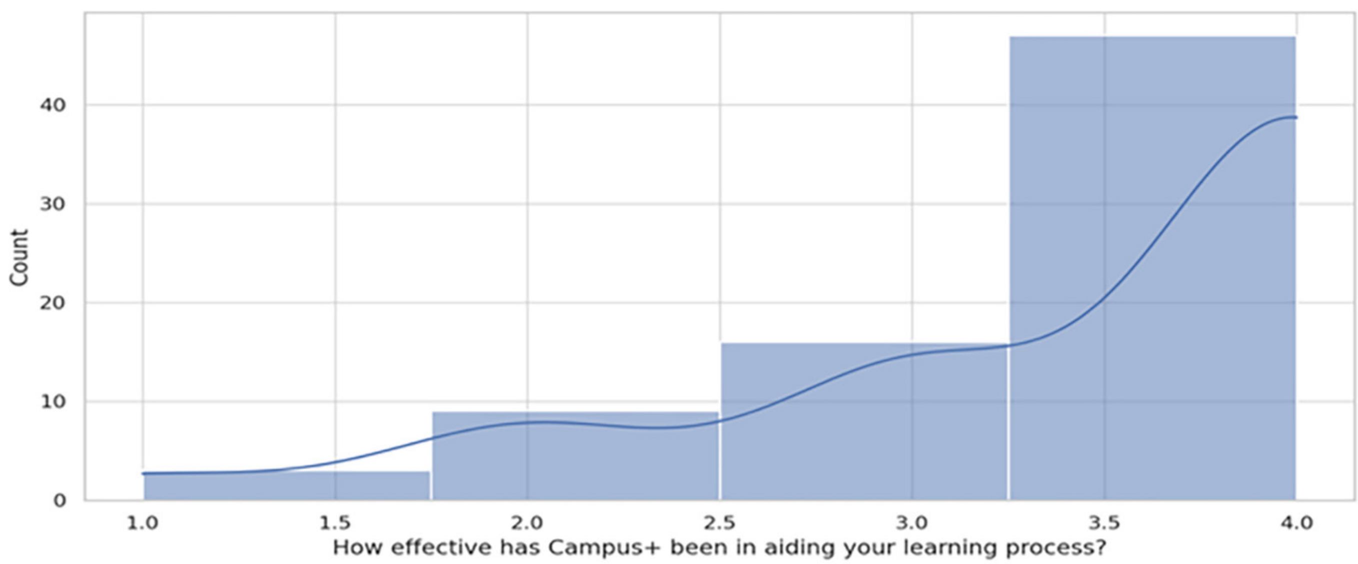

Fig. 4. How effective has Campus+ been in aiding your learning process?

After using Campus+, 80% of students reported feeling "slightly more engaged" or "highly engaged" with their studies. This demonstrates the platform's ability to promote engagement and active learning.

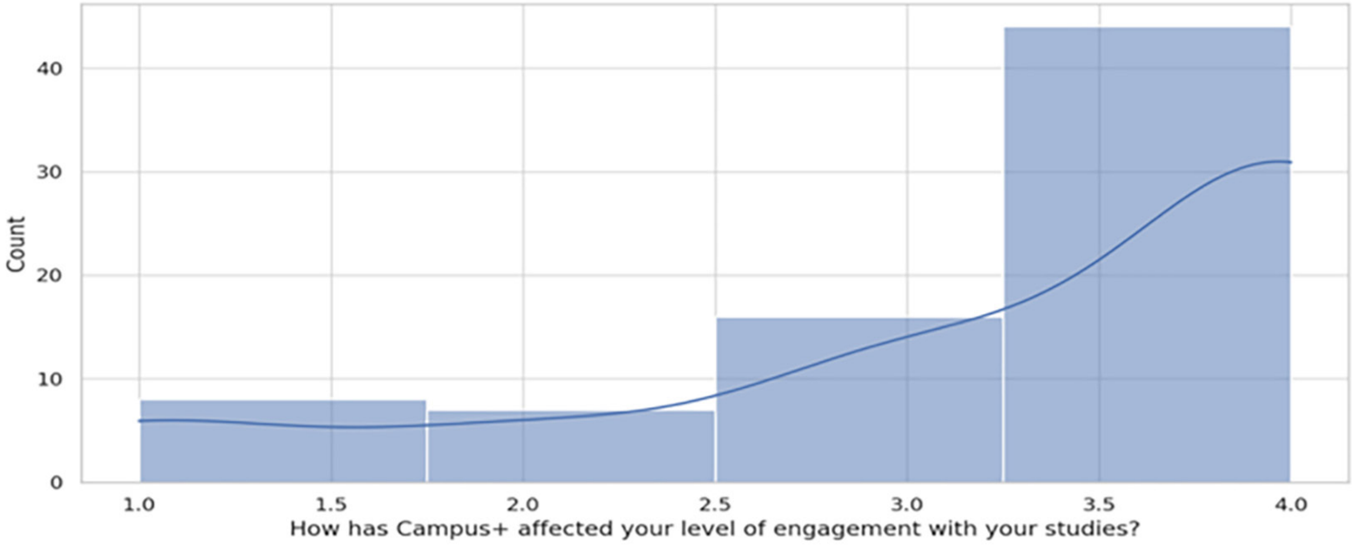

Fig. 5. How has Campus+ affected your level of engagement with your studies?

73% of students reported that Campus+ has "somewhat increased" or "significantly increased" their enthusiasm to learn. It demonstrates that the platform can be a major motivator for students to pursue their academic objectives.

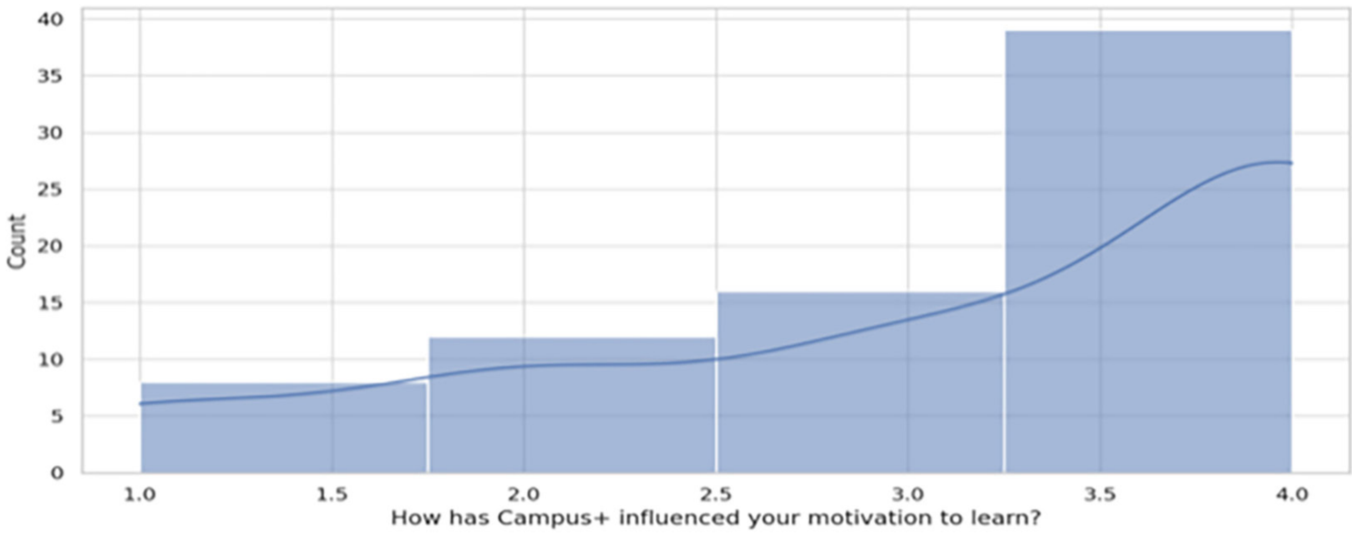

Fig. 6. How has Campus+ influenced your motivation to learn?

Significantly, 80% of students reported that Campus+ provided "moderate retention" or "excellent retention" in helping them remember and retain course material, demonstrating the platform's effectiveness in aiding students in retaining information and improving memory.

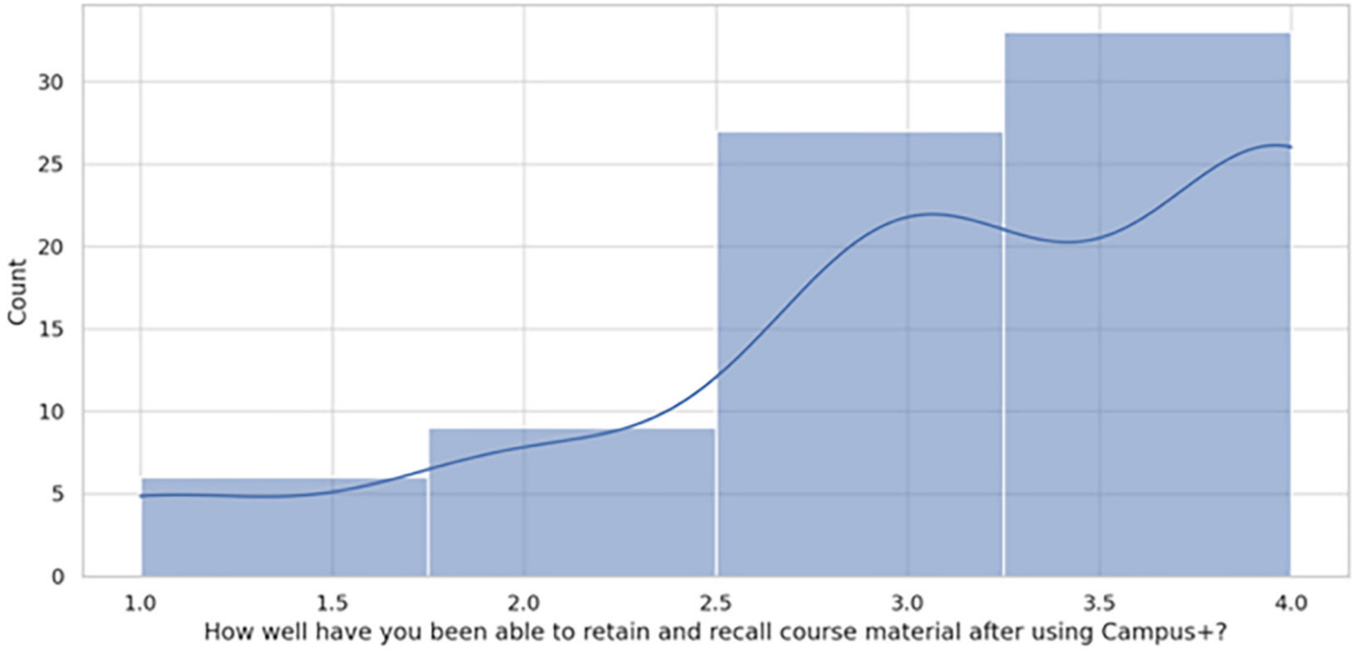

Fig. 7. How well have you been able to retain and recall course material after using Campus+?

88% of students rated Campus+ as "slightly better" or "far superior" compared to conventional teaching techniques, indicating that they viewed it as a valuable addition to their regular academic resources.

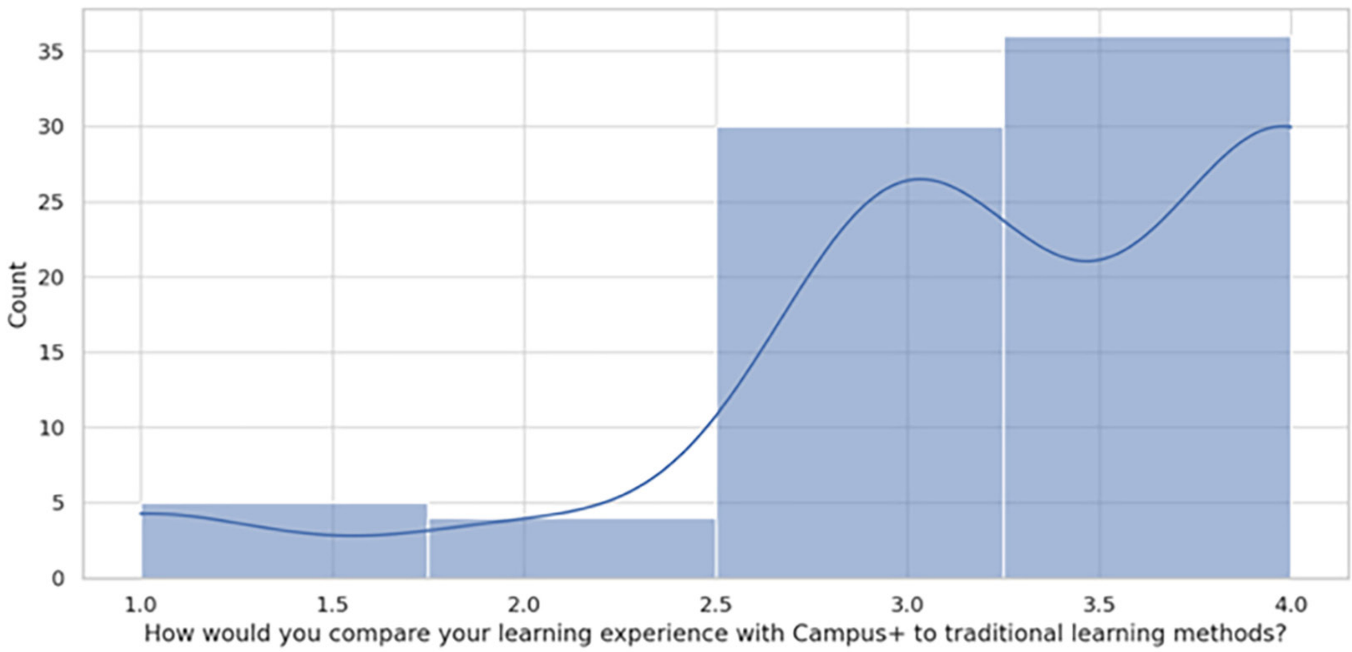

Fig. 8. How would you compare your learning experience with Campus+ to traditional learning methods?

The emphasis on the first level of Bloom's Taxonomy is a particularly intriguing aspect of this study. The foundation of cognitive learning processes is believed to be the level of knowledge, or the recall of factual information [29]. Further emphasizing the significance of mastering this level before advancing to higher cognitive skills such as understanding, applying, analyzing, evaluating, and producing [30]. Therefore, this study directly focuses on a crucial aspect of the student learning experience by evaluating the Campus+ system's ability to improve knowledge retention.

Furthermore, the research on how Campus+ affects knowledge recall may provide valuable insights into how it can eventually support more complex cognitive tasks. The results could impact instructional techniques across various disciplines and provide a guide for future system changes [31].

5 ETHICAL CONSIDERATIONS AND LIMITATIONS

Data security and ethical issues were the primary concerns throughout this study. We ensured that all participants in the study were informed about their rights, the purpose of the investigation, and the assurance that their data would be anonymized and protected in compliance with industry standards [32]. We also followed the principles of informed consent and voluntary participation outlined in the Helsinki Declaration.

On the other hand, the introduction of Campus+, an AI-powered educational platform, raises concerns about bias and impartiality. According to research by [33], AI systems may inadvertently perpetuate societal biases present in their training data. Therefore, instead of providing equal learning opportunities to all students, the system's recommendation and personalization features may perpetuate existing disparities in academic achievement among students from diverse populations.

The primary limitation of the present study is its focus on Bloom's taxonomy Level 1 (knowledge), which provides only a partial understanding of the learning outcomes. Future research should focus on higher-level cognitive abilities, such as application, analysis, and synthesis [30].

Additionally, a notable limitation of this study is attributed to the technical constraints of the model. The platform is not yet ready to handle graphics, numbers, and mathematical formulas. This could have an impact on the comprehensive delivery of courses, especially those that heavily rely on mathematical and graphic content. It may restrict the platform's applicability to a variety of courses, particularly those in the fields of science, mathematics, and engineering [34]. This may have an impact on the effectiveness of the learning experience. The platform should prioritize the ability to manage and convey complex graphical and mathematical content for future development in order to enhance its usability and usefulness across various academic fields.

Furthermore, the study's sample only included four academic programs, which may limit its ability to be widely generalized. Future studies should aim to incorporate a broader range of academic disciplines, larger sample sizes, and diverse educational settings.

The self-report survey methodology is also vulnerable to social desirability bias, leading respondents to overstate their positive experiences with the Campus+ platform while downplaying their negative ones [35]. Future research could integrate survey results with data from other sources, such as learning analytics and classroom observations, to offer a more comprehensive evaluation of the performance of the Campus+ platform.

6 CONCLUSION

The present study investigated the effectiveness of a personalized learning platform, Campus+, which employs AI technology, among undergraduate students in

Computer Science and Medical Sciences programs at Mohammed VI Polytechnic University. The study results suggest that the implementation of Campus+ had a positive impact on the academic achievement, engagement, and knowledge retention of students. The platform was found to be highly satisfactory by students in terms of its user-friendliness, effectiveness in facilitating the learning process, and ability to enhance engagement and motivation.

The findings indicate a clear advantage in incorporating personalized learning tools that utilize AI into the educational framework. Specifically, Campus+ shows promise for improving academic achievement. The implications of these findings are of great significance for institutions of higher education, especially at a time when the education sector is placing greater emphasis on digital transformation. The use of AI-powered platforms has been highlighted for their potential to enable personalized and adaptive learning, enhance student engagement and academic achievement, and supplement conventional teaching approaches.

Nonetheless, the research also highlights potential obstacles and ethical considerations, such as the risk of unintentional bias and the perpetuation of existing disparities in scholarly achievements. Consequently, it is imperative for educational institutions to consider these potential drawbacks when integrating AI-powered educational systems. It is crucial to implement appropriate measures and maintain ongoing oversight to ensure fairness and equality in educational opportunities.

The research study also presents several possibilities for future investigations and improvements of personalized learning systems driven by AI. One primary limitation of the research was its focus on the lower level of Bloom's taxonomy. Subsequent investigations should expand the scope of inquiry to assess the impact of these platforms on advanced cognitive abilities, such as application, analysis, synthesis, and evaluation. In addition, it is crucial to prioritize enhancing the platform's capacity to manage complex graphical and mathematical content, as this has the potential to increase its relevance across a wider range of academic disciplines.

Furthermore, it is advisable for future research efforts to incorporate broader and more diverse participant pools, encompassing various academic disciplines and educational settings, to enhance the relevance of the findings. The integration of additional data sources, such as learning analytics and classroom observations, has the potential to complement survey results and provide a more comprehensive understanding of the effectiveness of AI-powered personalized learning systems.

In conclusion, the present study offers compelling evidence of the potential benefits of AI-driven personalized learning systems, such as Campus+, in enhancing the quality of education. Nonetheless, it underscores the need for careful implementation, ongoing monitoring, and continuous improvement to enhance the effectiveness of these systems and ensure equality in educational outcomes.

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8 REFERENCES

[1] J. W. Keefe, "What is personalization?" *Phi Delta Kappan,* pp. 217–223, 2007. https://doi.org/10.1177/003172170708900312

[2] J. Hattie, *Visible Learning: A Synthesis of Over 800 Meta-Analyses Relating to Achievement*. Routledge, 2008.

[3] C. A. Tomlinson, *The Differentiated Classroom: Responding to the Needs of all Learners*. ASCD, 2014.

[4] R. M. and. S. L. K. Felder, "Learning and teaching styles in engineering education," *Engineering Education,* vol. 78, no. 7, pp. 674–681, 1988.

[5] S. J. Song, K. H. Tan, and M. M. Awang, "Generic digital equity model in education: Mobile-Assisted Personalized Learning (MAPL) through e-modules," *Sustainability,* p. 13, no. 19, p. 11115, 2021. https://doi.org/10.3390/su131911115

[6] E. L. Park and B. K. Choi, "Transformation of classroom spaces: Traditional versus active learning classroom in colleges," *Higher Education,* vol. 68, pp. 749–771, 2014. https://doi.org/10.1007/s10734-014-9742-0

[7] J. B. A. L. and C. R. R. Bransford, *How People Learn: Brain, Mind, Experience, and School*. National Academies Press, 2000.

[8] C. Dede, "Theoretical perspectives influencing the use of information technology in teaching and learning," in *International Handbook of Information Technology in Primary and Secondary Education,* J. Voogt and G. Knezek, Eds., 2008, pp. 43–62. https://doi.org/10.1007/978-0-387-73315-9_3

[9] A. Bhati and I. Song, "New methods for collaborative experiential learning to provide personalised formative assessment," *International Journal of Emerging Technologies in Learning (iJET),* vol. 14, no. 7, pp. 179–195, 2019. https://doi.org/10.3991/ijet.v14i07.9173

[10] A. G. Picciano, "The evolution of big data and learning analytics in American higher education," *Journal of Asynchronous Learning Networks,* vol. 18, no. 3, pp. 1–15, 2014.

[11] S. A. D. Popenici and S. Kerr, "Exploring the impact of artificial intelligence on teaching and learning in higher education," *Research and Practice in Technology Enhanced Learning,* vol. 12, no. 22, 2017. https://doi.org/10.1186/s41039-017-0062-8

[12] R. H. W. G. M. and F. L. B. Luckin, *Intelligence Unleashed: An Argument for AI in Education*. Pearson, 2016.

[13] Y. Shi and X. Yang, "A personalized matching system for management teaching resources based on collaborative filtering algorithm," *International Journal of Emerging Technologies in Learning (iJET),* vol. 15, no. 13, pp. 207–220, 2020. https://doi.org/10.3991/ijet.v15i13.15353

[14] B. P. Woolf, *Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing E-Learning*. Morgan Kaufmann, 2010.

[15] R. S. Baker and P. S. Inventado, "Educational data mining and learning analytics," in *Learning Analytics,* J. Larusson and B. White, Eds., pp. 61–75, 2014. https://doi.org/10.1007/978-1-4614-3305-7_4

[16] A. I. M. and B. Z. Klašnja-Milićević, "E-Learning personalization based on hybrid recommendation strategy and learning style identification," *Computers & Education,* vol. 112, pp. 48–62, 2017.

[17] K. VanLehn, "The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems," *Educational Psychologist,* vol. 46, no. 4, pp. 197–221, 2011. https://doi.org/10.1080/00461520.2011.611369

[18] B. D. Nye, "Intelligent tutoring systems by and for the developing world: A review of trends and approaches for educational technology in a global context," *International Journal of Artificial Intelligence in Education,* vol. 25, pp. 177–203, 2015. https://doi.org/10.1007/s40593-014-0028-6

[19] A. C. Graesser, P. Chipman, B. C. Haynes, and A. Olney, "AutoTutor: An intelligent tutoring system with mixed-initiative dialogue," in *IEEE Transactions on Education,* vol. 48, no. 4, 2005, pp. 612–618. https://doi.org/10.1109/TE.2005.856149

[20] J. D. Fletcher, "Education and training technology in the military," *Science,* vol. 323, no. 5910, pp. 72–75, 2009. https://doi.org/10.1126/science.1167778

[21] G. Biswas, H. Jeong, John S. Kinnebrew, Brian Sulcer, and Rod Roscoe, "Measuring self-regulated learning skills through social interactions in a teachable agent environment," *Research and Practice in Technology Enhanced Learning,* vol. 5, no. 2, pp. 123–152, 2010. https://doi.org/10.1142/S1793206810000839

[22] Pinecone, "Vector search engine," 2023. [Online]. Available: https://www.pinecone.io/.

[23] T. B. Brown *et al.*, "Language models are few-shot learners," *arXiv.org*, 2020. https://arxiv.org/abs/2005.14165

[24] J. T. Roscoe, *Fundamental Research Statistics for the Behavioral Sciences (2nd ed.).* New York: Holt, Rinehart and Winston, 1975.

[25] T. C. K. C. G. and D. J. Mikolov, "Efficient estimation of word representations in vector space," *arXiv preprint,* no. arXiv:1301.3781, 2013.

[26] O. and G. Y. Levy, "Neural word embedding as implicit matrix factorization," in *Advances in Neural Information Processing Systems,* pp. 2177–2185, 2014.

[27] J. Pennington, R. Socher, and C. Manning, "GloVe: Global vectors for word representation," in *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP),* 2014, pp. 1532–1543. https://doi.org/10.3115/v1/D14-1162

[28] A. Field, "Discovering statistics using IBM SPSS statistics," *Sage,* 2013.

[29] B. S. Bloom, "Taxonomy of educational objectives," *Cognitive Domain. McKay.,* vol. 1, 1956.

[30] D. R. Krathwohl, "A revision of Bloom's taxonomy: An overview," *Theory into Practice,* vol. 41, no. 4, pp. 212–218, 2002. https://doi.org/10.1207/s15430421tip4104_2

[31] R. Bensona and G. Samarawickrema, "Addressing the context of e-learning: Using transactional distance theory to inform design," *Distance Education,* vol. 30, no. 1, pp. 5–21, 2009. https://doi.org/10.1080/01587910902845972

[32] K. Kaiser, "Protecting respondent confidentiality in qualitative research," *Qualitative Health Research,* vol. 19, no. 11, pp. 1632–1641, 2009. https://doi.org/10.1177/1049732309350879

[33] A. Caliskan, J. B. Bryson, and A. Narayanan, "Semantics derived automatically from language corpora contain human-like biases," *Science,* vol. 356, no. 6334, pp. 183–186, 2017. https://doi.org/10.1126/science.aal4230

[34] A. Bozkurt, "Emergency remote teaching in a time of global crisis due to coronavirus pandemic," *Asian Journal of Distance Education,* vol. 15, no. 1, pp. i–vi, 2020.

[35] R. J. Fisher, "Social desirability bias and the validity of indirect questioning," *Journal of Consumer Research,* vol. 20, no. 2, pp. 303–315, 1993. https://doi.org/10.1086/209351

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