Remittances Review
April 2024,
Volume: 9, No: 2, pp.5136-5149
ISSN: 2059-6588(Print) | ISSN 2059-6596(Online)
Received : 20 March 2024, Accepted: 30 April 2024
DOI: https://doi.org/10.33282/rr.vx9i2.271

A Study on the Impact of Artificial Intelligence on Students Personalized Learning Experiences in Online Distance Learning Institutions of Pakistan

Darakhshan Muslim*[1,3], Muhammad Sarwar[1], Muhammad Arif[1], Maqbool Hussain Sial[2], Meimoona Riaz[3] and Gulbadin Khan[4]

[1]Department of Education, Superior University Lahore.

[2]Department of Economics and Quantitative Methods, University of Management and Technology Lahore.

[3]Department of Education, Virtual University Lahore.

[4]Government College University Faisalabad.

*Corresponding Author: darakhshan.zahid@vu.edu.pk

Abstract

The aim of this study is to investigate the impact of artificial intelligence on students' personalized learning experiences in online distance learning institutions in Pakistan. A survey questionnaire was administered to a sample of online distance learning students to gather data. Data was analyzed by using Structure equation modeling (SEM) to determine the relationship between latent variables related to personalized learning, i.e. interaction and engagement, academic support, and overall satisfaction among students. The findings of this study provide valuable insights in defining the complex relationship between the above stated variables. Findings of this study support the importance of using Artificial intelligence in enhancing the student's personalized learning, interaction & engagement, academic support and promoting student satisfaction and success. Institutions and educators should consider incorporating these elements into their educational practices to enhance the overall student experiences and satisfaction.

Key Words: Artificial Intelligence, Personalized Learning, Online Distance Learning

Remittances Review
April 2024,
Volume: 9, No: 2, pp.5136-5149
ISSN: 2059-6588(Print) | ISSN 2059-6596(Online)

Introduction

The integration of artificial intelligence in education has emerged as a new trend nowadays. Education has been hugely revolutionized by artificial intelligence (AI). In online and distance learning, AI has the potential to greatly improve personalized learning experiences for students. The purpose of this study is to investigate the impact of artificial intelligence on the personalized learning experiences of online students. Also, the aim is to understand the effect of this integrated approach on the motivation level and student engagement in online mode of education. Online learning systems can analyze a lot of data to get insights into students' learning patterns and preferences due to the immense use of artificial intelligence tools. This allows the students to adapt instructional content according to the individual needs of each student. AI can provide individualized recommendations, adaptive assessments, and focused feedback to online distance learning students (Hesham et al.,2023). This study contributes to the body of knowledge related to using educational technology or AI in enhancing the student's personalized learning experiences and support the continuous improvement and overall satisfaction.

Personalized learning is an educational approach that tailors instruction to the individual needs, interests, and abilities of each student. With the advancement of online distance learning, personalized learning has become even more crucial in ensuring student engagement and success.

Online distance learning integrated with AI systems can provide more individualized learning experiences and can enhance the student-teacher interaction, but there are challenges about social boundaries. While AI system has improved providing personalized support and both the amount and quality of communication, there are certain possible concerns that should be considered, such as privacy, biasness, accountability etc. (Seo et al., 2021)

Artificial Intelligence is an important technique for enhancing learning outcomes when used in personalized education. AI-driven adaptive learning systems can adjust a task's

Volume: 9, No: 2, pp.5136-5149
ISSN: 2059-6588(Print) | ISSN 2059-6596(Online)

complexity based on a student's performance. Because of this flexibility, students can go at their own pace, which could help them understand and remember the material better. (Holmes et al., 2019)

Research suggests that AI tools can boost student participation, which is necessary for effective learning. AI-powered learning platforms employ various techniques such as gamification, interactive content, and real-time feedback to maintain student engagement. For instance, interactive assignments and gamified elements in AI apps significantly increase student interaction and engagement (Luckin et al., 2016).

The potential of AI in personalized learning is to make education more accessible, which is one of its most significant impacts. Personalized learning experiences for students with diverse needs, including those with disabilities, can be provided by AI. The ability of AI-driven tools to provide personalized learning materials includes text-to-speech for visually impaired students and adaptive text sizes for those with dyslexia, thus fostering inclusive education. (Xu and Yang, 2020)

Personalized learning represents a transformative approach in education, leveraging technology to tailor educational experiences of individual student needs. While this approach promises significant benefits, it also raises critical, ethical and privacy concerns. The ethical implications of personalized learning encompass issues of consent, data ownership, equity, and access (Selwyn, 2016; Eynon, 2019). Data collection in personalized learning systems raises concerns about informed consent, data ownership, and control (Williamson, 2017). Moreover, the potential for data breaches and long-term privacy impacts underscores the need for robust security measures and transparency (Schiff, 2020; Westin, 2018).

The impact of AI on personalized learning is profound, with significant improvements in learning outcomes, student engagement, and accessibility. However, to fully realize the potential of AI in education, stakeholders must address the associated challenges and ensure that these technologies are implemented ethically and equitably.

Volume: 9, No: 2, pp.5136-5149
ISSN: 2059-6588(Print) | ISSN 2059-6596(Online)

Research Objectives:

The objective of this study is to:

- assess the effectiveness of artificial intelligence in enhancing personalized learning experiences for online distance learning students
- identify the areas of online distance learning where artificial intelligence can be integrated for better personalized learning experiences of students
- evaluate the impact of artificial intelligence on student engagement and motivation in online distance learning environment

Research Hypothesis

H_1: The integration of artificial intelligence positively impacts students' personalized learning experiences in online distance learning mode of education.

H_2: The use of artificial intelligence leads towards a better and improved adaptability of educational content in students' personalized learning experience.

H_3: Students who are using artificial intelligence with their personalized experiences have higher engagement and motivation level in online institutions of Pakistan.

Significance of the Study

The significance of this study lies in the importance of using artificial intelligence to improve personalized learning experiences in Pakistani online distance learning institutions. By examining the impact of AI on personalized learning, the study can provide valuable insights into how AI can be effectively integrated into educational settings to enhance student engagement and improve academic performance. Additionally, research may have a significant impact on Pakistani education in the future by opening doors for online distance learning institutions to provide their students with more effective and interesting learning opportunities. Also, the study provides the potential information to enhance the personalized learning experiences of online students by using artificial intelligence. The findings of this study can also help inform the development of policies and strategies for integrating AI into online distance

Volume: 9, No: 2, pp.5136-5149
ISSN: 2059-6588(Print) | ISSN 2059-6596(Online)

learning institutions in Pakistan, ultimately contributing to the enhancement of educational quality and the advancement of digital learning technologies

Research Methodology

This study employed a quantitative research design using Structural Equation Modeling (SEM) to test hypothesized relationships between latent variables related to personalized learning, interaction and engagement, academic support, and overall satisfaction among students. The SEM technique was chosen for its ability to analyze complex relationships between observed and latent variables simultaneously.

The study involved a sample of 100 students from online distance learning institutions of Pakistan. Participants were selected using a simple random sampling technique to ensure a representative sample across different demographics, including age, gender, academic discipline, and level of study. All participants were provided with informed consent before taking part in the study. Data was collected through a structured questionnaire comprising validated scales to measure the latent variables.

Initial analysis involved calculating descriptive statistics (mean, standard deviation) for each variable to understand the basic characteristics of the data. Composite Reliability (CR) was used to assess the internal consistency of each factor, with a threshold of 0.7 indicating acceptable reliability. Average Variance Extracted (AVE) was used to evaluate convergent validity, with values above 0.5 considered acceptable. Discriminant Validity was assessed using the Fornell-Larcker criterion to ensure that constructs were distinct from each other. Structural Equation Modeling (SEM) was tested using SEM, which included the path analysis to examine direct relationships between personalized learning, interaction and engagement, academic support, and overall satisfaction.

Findings

Descriptive statistics of the data shows a slight majority of females (59%). The majority of respondents are between 31-40 years old (61%), followed by those aged 20-30 (37%). Most respondents hold an MS/MPhil degree (72%), with smaller percentages holding a bachelor’s degree (13%) or a PhD (15%). Respondents are spread across different levels of work experience, with the largest group having less than 5 years of experience (37%).

Volume: 9, No: 2, pp.5136-5149
ISSN: 2059-6588(Print) | ISSN 2059-6596(Online)

Table 1: Correlation Table

	ASA	I&E	OS	PL
Academic Support and Assistant	1			
Interaction and Engagement	0.884	1		
Overall Satisfaction	0.775	0.911	1	
Personalized Learning	0.835	0.862	0.847	1

Table 1 demonstrates that high correlations exist between Interaction and Engagement and other variables, particularly Overall Satisfaction (0.911), indicating that interaction and engagement significantly impact overall satisfaction.

Personalized Learning also shows strong correlations with other variables, especially Interaction and Engagement (0.862) and Overall Satisfaction (0.847), suggesting that personalized learning is closely related to both engagement and overall satisfaction. Academic Support and Assistance shows substantial correlations with all other variables, particularly with Interaction and Engagement (0.884) and Personalized Learning (0.835), indicating the importance of academic support in engagement and personalized learning.

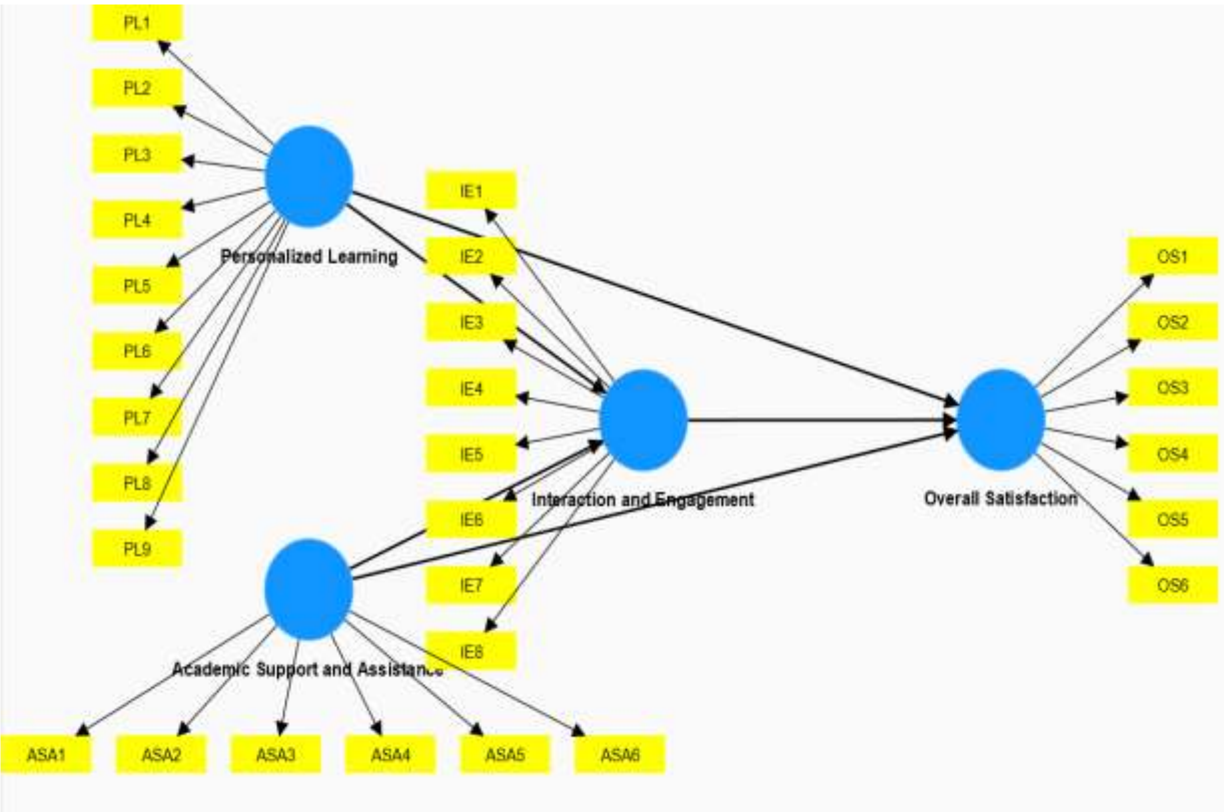

Figure 1. Proposed SEM Model

Remittances Review
April 2024,
Volume: 9, No: 2, pp.5136-5149
ISSN: 2059-6588(Print) | ISSN 2059-6596(Online)

Confirmatory Factor Analysis (CFA) is a measurement model comprised of a set of equations that specify the relationships between the observed variables and the latent variables that they are supposed to measure. The factor loadings in Figure 1 show the strength of the relationship between each variable and its corresponding factor. From Table 2 and 3 we can see that factor loading in all factors is greater than 0.7 which indicates a strong relationship between the variable and the factor. Whereas a factor loading of 0.308 for Personalized Learning and Overall Satisfaction and 0.242 indicates a moderate relationship between Academic support and assistance and Overall Satisfaction.

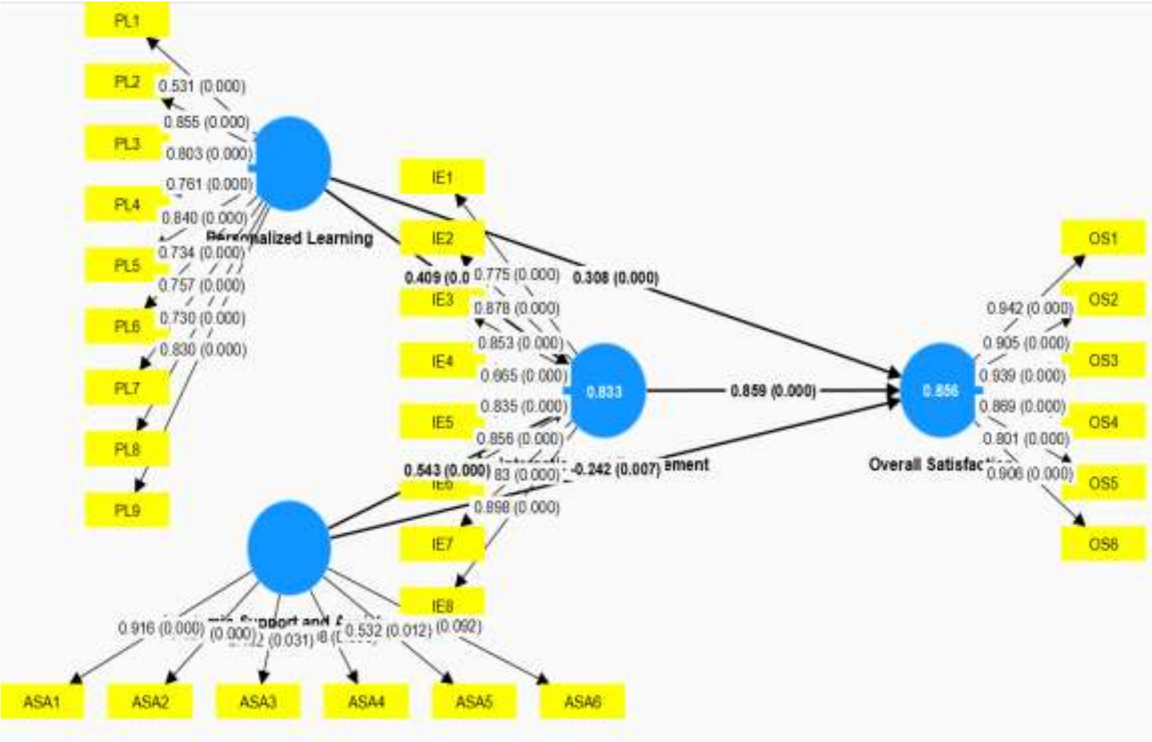

Figure 2. Proposed Model with Path Coefficients

Table 2. Path Coefficients

	Original sample (O)
ASA1 <- Academic Support and Assistance	0.916
ASA2 <- Academic Support and Assistance	0.824
ASA3 <- Academic Support and Assistance	0.852
ASA4 <- Academic Support and Assistance	0.898
ASA5 <- Academic Support and Assistance	0.832
ASA6 <- Academic Support and Assistance	0.741
IE1 <- Interaction & Engagement	0.775
IE2 <- Interaction & Engagement	0.878
IE3 <- Interaction & Engagement	0.853
IE4 <- Interaction & Engagement	0.865
IE5 <- Interaction & Engagement	0.835
IE6 <- Interaction & Engagement	0.856
IE7 <- Interaction & Engagement	0.883
IE8 <- Interaction & Engagement	0.898
OS1 <- Overall Satisfaction	0.942
OS2 <- Overall Satisfaction	0.905
OS3 <- Overall Satisfaction	0.939
OS4 <- Overall Satisfaction	0.869
OS5 <- Overall Satisfaction	0.801
OS6 <- Overall Satisfaction	0.906
PL1 <- Personalized Learning	0.831
PL2 <- Personalized Learning	0.855
PL3 <- Personalized Learning	0.803
PL4 <- Personalized Learning	0.761
PL5 <- Personalized Learning	0.840
PL6 <- Personalized Learning	0.734
PL7 <- Personalized Learning	0.757
PL8 <- Personalized Learning	0.730
PL9 <- Personalized Learning	0.830

Table 3: Path Coefficient Analysis

Path coefficients - Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Academic Support and Assistance -> Interaction and Engagement	0.543	0.545	0.087	6.276	0.000
Academic Support and Assistance -> Overall Satisfaction	0.242	0.226	0.089	2.711	0.007
Interaction and Engagement -> Overall Satisfaction	0.859	0.841	0.093	9.209	0.000
Personalized Learning -> Interaction and Engagement	0.409	0.409	0.088	4.621	0.000
Personalized Learning -> Overall Satisfaction	0.308	0.313	0.076	4.069	0.000

The model is indeed a path analysis diagram showing a mediation model. From the **Table 2-3** and **Figure 1-3**; we can see the following findings:

Personalized Learning -> Interaction & Engagement (path coefficient: 0.409, p-value: 0.000) - This path shows a positive and statistically significant relationship between personalized learning and interaction and engagement. In other words, students who experience more personalized learning are also more likely to report higher levels of interaction and engagement with academic support and assistance.

Personalized Learning -> Overall Satisfaction (path coefficient: 0.308, p-value: 0.000) - This path shows a positive and statistically significant relationship between personalized learning and overall satisfaction. In other words, students who experience more personalized learning are also more likely to report higher levels of overall satisfaction.

Interaction & Engagement -> Overall Satisfaction (path coefficient: 0.543, p-value: 0.000) - This path shows a positive and statistically significant relationship between interaction & engagement and overall satisfaction. In other words, students who report higher levels of interaction and engagement with academic support and assistance are also more likely to report higher levels of overall satisfaction.

Academic Support and Assistance -> Interaction & Engagement (path coefficient: 0.242, p-value: 0.007) - This path shows a positive and statistically significant relationship between academic support and assistance and interaction/engagement. This seems counter-intuitive, but it might be due to a suppressor effect. A suppressor effect arises when a third variable, not included in the model, influences both the independent and dependent variables. In this case, it’s possible that there’s a third variable that makes students who need less academic support and assistance more likely to interact and engage with those services.

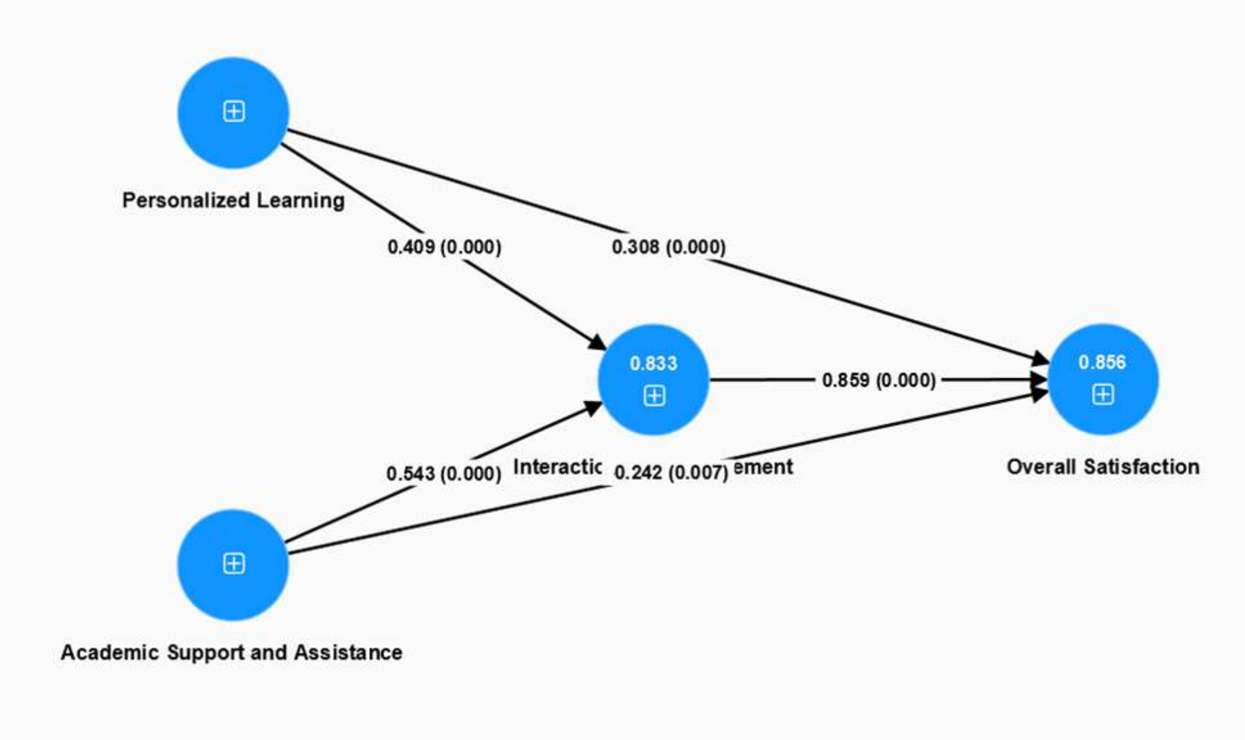

Figure 3. Proposed Model with Path Coefficients and P values

From **Table 4** we can see that Composite reliability (CR) of 0.7 is obtained that shows that the constructs are measuring the underlying concepts they are intended to represent. For all constructs, an Average variance extracted AVE of 0.5 or higher is obtained that indicates the constructs are explaining at least 50% of the variance in their respective items, suggesting good convergent validity. Only Academic Support and Assistance shows the AVE is less than 0.5. This construct may not explain as much of the variance in its items as desired.

Table 4: Construct Reliability and Validity

Construct reliability and validity - Overview

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Academic Support and Assistance	0.803	0.909	0.836	0.488
Interaction and Engagement	0.936	0.943	0.948	0.695
Overall Satisfaction	0.950	0.956	0.960	0.801
Personalized Learning	0.910	0.923	0.926	0.586

Table 5: Discriminant Validity

Discriminant validity - Fornell-Larcker criterion

	Academic Support and Assistance	Interaction and Engagement	Overall Satisfaction	Personalized Learning
Academic Support and Assistance	0.699			
Interaction and Engagement	0.884	0.833		
Overall Satisfaction	0.775	0.911	0.895	
Personalized Learning	0.835	0.862	0.847	0.766

From **Table 5** we can see that the Constructs values are greater than 0.450 discriminant validity, it shows that the constructs are sufficiently different from each other, confirming that they are measuring unique aspects or characteristics.

Alignment of Objectives with the Findings

Objective 1: Assess the effectiveness of AI in enhancing personalized learning experiences for online distance learning students

The findings of following tables are aligned with the objective 1:

1. Correlation Table (Table 1): High correlation between Personalized Learning and Interaction & Engagement (0.862) and Overall Satisfaction (0.847).

2. Path Coefficient Analysis (Tables 2-3): Positive and significant relationship between Personalized Learning and both Interaction & Engagement (path coefficient: 0.409) and Overall Satisfaction (path coefficient: 0.308).

Objective 2: Identify areas in online distance learning where AI can be integrated for better personalized learning experiences of students

The findings of following tables are aligned with the objective 2:

1. Correlation Table (Table 1): Indicates that areas such as Interaction & Engagement and Academic Support are crucial for enhancing personalized learning.

Objective 3: Evaluate the impact of AI on student engagement and motivation in online distance learning environment

The findings of following tables are aligned with the objective 3:

1. Correlation Table (Table 1): High correlation between Interaction & Engagement and Overall Satisfaction (0.911).

2. Path Coefficient Analysis (Tables 2-3): Positive and significant relationship between Interaction & Engagement and Overall Satisfaction (path coefficient: 0.543), and between Academic Support and Interaction & Engagement (path coefficient: 0.242).

The tables in the study primarily align with the objectives focused on evaluating the effectiveness of AI in enhancing personalized learning experiences (Objective 1) and assessing the impact of AI on student engagement and motivation (Objective 3). The descriptive measures stated at the start of the findings also provide foundational data that can inform strategies for AI integration (Objective 2).

Discussion

The Findings of the study demonstrates the importance of personalized learning and engagement in boosting student satisfaction . The study shows a significant relationship between personalized learning , interaction & engagement , academic support and assistance, and overall satisfaction. Specifically, personalized learning has a positive impact on both interaction & engagement and overall satisfaction. Interaction & engagement also positively influences overall satisfaction . Although academic support positively impacts engagement, there may be unmeasured factors influencing this relationship. Fostering personalized learning and engagement is crucial for improving student satisfaction.

Conclusion

To conclude we can say that personalized learning , interaction & engagement , and academic support and assistance, all play important roles in shaping students' overall satisfaction . The strong relationship between interaction & engagement and overall satisfaction indicates the importance of providing students with opportunities to actively engage with academic support services.

Personalized learning recognizes the unique requirements and preferences of each student, it is essential for promoting student engagement and satisfaction. Personalized learning can boost confidence and motivation in students, which will ultimately result in better academic performance.

Volume: 9, No: 2, pp.5136-5149
ISSN: 2059-6588(Print) | ISSN 2059-6596(Online)

Recommendations

1. Online distance learning institutions and policy makers must incorporate more advanced artificial intelligence tools to enhance the personalized learning of students.
2. More trainings must be arranged on a broader level to equip our teachers with the modern trends of artificial intelligence and its integration in educational process.
3. A culture of continuous improvement and motivation along with the enhancement of interaction and engagement must prevail in online distance learning institutions.

References

1. Ahmad, S. F., Han, H., Alam, M. M., Rehmat, M., Irshad, M., Arraño-Muñoz, M., & Ariza-Montes, A. (2023). Impact of artificial intelligence on human loss in decision making, laziness and safety in education. *Humanities and Social Sciences Communications*, *10*(1), 1-14.
2. Ahmad, S. F., Rahmat, M. K., Mubarik, M. S., Alam, M. M., & Hyder, S. I. (2021). Artificial intelligence and its role in education. *Sustainability*, *13*(22), 12902.
3. Das, A., Malaviya, S., & Singh, M. (2023). The impact of AI-driven personalization on learners' performance. *International Journal of Computer*.
4. Hesham, A., Dempere, J., Akre, V., & Flores, P. (2023, November). Artificial Intelligence in Education (AIED): Implications and Challenges. In Allam, Hesham, Dempere, Juan, Akre, Vish, & Flores, Pedro.(2023). Artificial Intelligence in Education (AIED): Implications and Challenges. In Proceedings of the HCT International General Education Conference (HCT-IGEC 2023) (pp. 126-140).
5. Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Center for Curriculum Redesign.
6. Kumar, V., & Mehta, K. (2017). AI and Education: The Role of Artificial Intelligence in Personalized Learning. Journal of Educational Technology, 14(3), 12-25.

7. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). Intelligence Unleashed: An Argument for AI in Education. Pearson Education.
8. Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, *12*(1), 1-13.
9. Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner–instructor interaction in online learning. *International journal of educational technology in higher education*, *18*(1), 1-23.
10. Schiff, D. (2020). Out of the loop: How algorithms and AI are undermining our education system. Technology in Society, 60, 101221.
11. Williamson, B. (2017). Big data in education: The digital future of learning, policy, and practice. SAGE Publications.
12. Williamson, B. (2018). The hidden architecture of higher education: Building a big data infrastructure for the 'smarter university'. International Journal of Educational Technology in Higher Education, 15(1), 12.
13. Xu, Y., & Yang, Y. (2020). Application of Artificial Intelligence in Education: A Review. Journal of Educational Research and Development, 6(2), 45-56.