European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk

Effectiveness of Artificial Intelligence in Higher Education: A SEMANN Approach from Students' Perspectives

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Abstract:
This study explores the effectiveness of Artificial Intelligence (AI) in higher education, focusing on Accuracy and Reliability (AR) and Responsiveness (RS) as determinants of Overall Effectiveness of AI (OEAI). Employing a dual analytical approach of Structural Equation Modeling (SEM) and Artificial Neural Network (ANN) analysis, for the validate of two hypotheses. H1: establishes a significant positive impact of AR on OEAI, supported by a path coefficient ($\beta = 0.706$; $t = 15.097$). H2: confirms a positive influence of RS on OEAI, albeit with lower values ($\beta = 0.119$; $t = 2.466$), suggesting a lesser impact on students' overall perception. Reliability and validity analyses ensure the robustness of this research model, validating convergent and discriminant validity. Neural network analysis underscores the importance of AR and RS, with AR identified as the most influential factor (100%), followed by RS (68%). The model exhibits high accuracy ($R^2 = 0.895$), confirming its predictive power.

Keywords: Artificial Intelligence, Higher education, Structural equation modeling, Artificial Neural Network

1. Introduction

In today's world, humans are deeply enmeshed in a society that is steadily becoming more involved in a broad technological evolution (Alnaqbi & Yassin, 2021). Artificial Intelligence (AI) is a pervasive concept and tool that has become an inherent aspect of quotidian life, deeply integrated into various facets of society (Southworth et al., 2023). Meanwhile, it has revolutionized various aspects of human existence, excelling beyond human capabilities (Rybinski & Kopciuszewska, 2021). At the same time AI has become an important tool in higher education, offering advantages for both teachers and students. It allows for the automation of repetitive tasks, freeing up time for more meaningful learning (Valencia Chica et al., 2023). Moreover, AI has become a transformative influence in the education sector, providing inventive solutions to elevate both teaching and learning encounters by introducing the potential for personalized and adaptive learning, streamlining administrative processes, and facilitating data-driven decision-making (Sharma & Sharma, 2023). But, AI integration in higher education faces several challenges. One major concern is the potential for biased algorithms, especially in admission and grading processes, which could have negative effects on students (Seven Global AI Ethics Policies, 2023). Another challenge is the substitution of human educators with AI systems, raising questions about transparency and accountability in decision-making processes (Popenici, 2023). Additionally, there are concerns about the ethical implications of AI, including issues of privacy, accuracy, and the impact on personal

development and societal values (Chan & Hu, 2023). Educators are also uncertain about how to effectively harness AI's pedagogical advantages on a larger scale and its potential impact on teaching and learning (Sharma & Sharma, 2023). Furthermore, the integration of AI in higher education must address the unique challenges faced by international students, such as privacy concerns, cultural differences, and language proficiency (Wang et al, 2023). Overall, stakeholders must work together to ensure responsible AI deployment in higher education, considering fairness, transparency, and maximizing benefits while minimizing risks. Hence, our endeavour is to explore the dimension concern with these challenges as well as to develop an effective model to enhance the effectiveness of AI, integrating in higher education.

2. Literature review

2.1 Artificial intelligence and higher education efficiency

Artificial intelligence (AI) plays a pivotal role in enhancing the efficiency of higher education. By automating administrative tasks, AI allows educators to redirect their time towards more meaningful endeavours such as designing curriculum and providing individualized attention to students (Chica et al., 2023). Furthermore, AI facilitates data analysis and pedagogical reporting, empowering evidence-based decision-making in educational institutions (Guerrero-Quiñonez et al., 2023). Additionally, the transformative impact extends to personalize learning experiences, where AI adapts educational processes to meet individual student needs, delivering relevant content and real-time personalized feedback (Zouhaier, 2023). Integrated AI-assisted teaching-learning frameworks have emerged, revolutionizing traditional schooling with a more efficient, adaptable, and effective educational model (Slimi, 2023). The integration of AI in higher education has the potential to transfigure teaching methods, offering personalized approaches, timely feedback, and streamlined administrative tasks (Chang et al., 2022). Artificial intelligence will enhance uniformity and precision in educational programs and enrolment processes (Ma & Siau, 2018). Moreover, the AI-driven college education system enhances students' technical foundation, with superior practical teaching effectiveness, increased popularity, higher evaluation scores, and overall improvement in quality and innovation ability (Zhang, 2022). Overall, AI in higher education offers advantages such as automation of tasks; personalization of learning, and improved efficiency and quality, but ethical and privacy challenges need to be addressed. On the other hand, Yousif et al., 2011 assert that there is notable shift in the educational landscape, emphasizing a growing trend towards heightened interactivity and engagement in the modern learning experience. AI interactive technology has been applied to model the teaching interactive process, resulting in the design of an interactive teaching and learning system for students (Liu & Zou, 2022).

2.1 Artificial intelligence and students' performance

Artificial Intelligence (AI) has become increasingly prevalent in the realm of education, specifically for forecasting and assessing students' academic performance. Employing AI techniques, particularly machine learning algorithms, educators can analyse vast datasets to make accurate predictions regarding students' academic outcomes (Halagatti et al., 2023; Hoti et al., 2023; Wang, 2023; Sarra et al., 2019; Jain & Solanki, 2019). These predictions serve as valuable tools for educators, aiding in the early identification of students who may be at risk of dropping out and enabling the provision of targeted support (Ghashout et al., 2023; Oladokun et al., 2008). The integration of artificial intelligence has proven to be instrumental in boosting student engagement, enhancing collaborative learning performance, and reinforcing overall student satisfaction with the educational process (Ouyang et al., 2023).

Similarly, AI chatbots improve academic performance, self-efficacy and motivation by facilitating active student engagement through effective feedback and fostering a positive interaction (Lee et al., 2022).

3. Objectives and hypotheses development

Quality education is vital for national development (Batra et al., 2023), achievable through advanced technologies like artificial intelligence (Cremer and Bettignies, 2013). Students prefer future-oriented, active learning with positive outcomes, where ICT technologies, including AI, enhance learning (Vaclavik et al., 2022). Telford and Masson (2005) connect evaluating educational quality to students' expectations. The study explores AI effectiveness in higher education from students' perspectives with two hypotheses.

H1: Accuracy and Reliability (AR) of AI positively impact Overall Effectiveness of Artificial Intelligence (OEAI) in higher education.

Studies emphasize the critical role of accurate and reliable AI models in education, enhancing outcomes (Dignum, 2018; Li et al., 2020; Siemens & Long, 2011; Baker & Inventado, 2014).

H2: Responsiveness (RS) of AI positively influences OEAI in higher education.

Responsiveness is crucial for user satisfaction; in education, timely and context-aware interactions positively impact effectiveness.

The research aims to offer practical insights for policymakers and educators to improve AI implementation in higher education, specifically focusing on AR and RS positively affecting OEAI. Rigorous statistical analyses and model evaluations will ensure robust and reliable findings. The details of the constructs and the questionnaire are in Annexure - 1.

4. Research methodology

This research adopts a mixed-methods approach to investigate factors influencing the effectiveness of Artificial Intelligence (AI) in higher education. Utilizing a 5-point Likert scale, data from 214 responses of 2nd year students of Veer Surendra Sai University of Technology, Burla, Odisha, out of a target population of 500 students, will be collected via a survey. This study employs a dual analytical approach, combining Structural Equation Modeling (SEM) and Artificial Neural Network (ANN) analysis, a key artificial intelligence technique (Chan & Chong, 2012). While traditional linear techniques like SEM may oversimplify complex decision-making processes due to their limitation in detecting only linear relationships (Chan & Chong, 2012; Sim et al., 2014; Tan et al., 2014), the ANN model is introduced to identify non-linear relationships and provide increased accuracy in predictions (Tan et al., 2014; Chong, 2013; Sim et al., 2014).

Using a dual-phase methodology, SEM was first used to test the overall research model and identified prominent predictors. Subsequently, these predictors were utilized as inputs for the ANN model, allowing determination of their relative importance (Leong et al., 2013; Tan et al., 2014). The ANN model, implemented using the Keras library in Python, underwent comprehensive training and evaluation, incorporating both R and Python for Machine Learning Modeling (MLM). Various techniques were applied to enhance the model's robustness and effectiveness. The integration of SEM and ANN aims to provide a comprehensive understanding of the intricate dynamics impacting AI effectiveness in the higher education context.

5. Findings and discussion

5.1. Reliability and validity Analysis

Reliability, assessed via Cronbach's alpha, surpassed the threshold of 0.70 across all items, ensuring the robustness of the instrument (Table 1). Extracting three distinct factors (Factors with eigenvalue more than one in depicted in Scree plot (Figure - 1), from the PCA Varimax rotation matrix, each with factor loadings surpassing 0.5 (Table 2), underscored the questionnaire's robust validation, collectively elucidating 56% of the total variations. Subsequent scrutiny involved the validation of fitness indexes and rigorous testing of hypotheses. Confirmatory Factor Analysis (CFA) was executed to gauge the fidelity of well-defined variables in representing distinct factors, contributing to the methodological precision of the study.

To evaluate convergent validity, factors such as factor loadings, average variance extracted (AVE), and composite reliability (CR) were considered (Hair et al., 2021). The AVE consistently exceeded the recommended 0.50 threshold, and CR values surpassed the 0.70 threshold (Table 2) for all constructs (Henseler & Chin, 2010). Factor loadings were above 0.5 (Table 2), confirming convergent validity (Chin, 1998; Hair et al., 2013). For discriminant validity, the heterotrait–monotrait ratio (HTMT) with bootstrap confidence intervals, as proposed by Henseler et al. (2015), was employed. The model, bootstrapped through SeminR, demonstrated discriminant validity with HTMT below 1.0 (Table 3) at a 95% confidence interval (Henseler et al., 2015; Franke and Sarstedt, 2019).

5.2. Testing of Hypotheses and Structural Equation Modelling

To examine research model, leveraging SeminR for precise latent variable score estimation and advanced bootstrapping for scrutiny. Thorough assessment of two hypotheses, proposing direct relationships between key constructs, revealed significant outcomes. All hypotheses were validated, summarized in Tables 4 and Figure 2.

The comprehensive examination of the research model, delved into hypotheses offering unique insights into the intricate dynamics of Overall Effectiveness of Artificial Intelligence (OEAI) and its determinant factors. Hypothesis H1, depicting that Accuracy and reliability (AR) of AI positively influence the Overall Effectiveness of Artificial Intelligence (OEAI). H1 had a statistically significant path coefficient (β=0.706; t=15.097). Again, H2, was also accepted which shows that Responsiveness (RS) of AI positively influence the Overall Effectiveness of Artificial Intelligence (OEAI) despite lower values (β=0.119; t=2.466), indicating a lesser impact on overall Effectiveness of Artificial Intelligence in higher education.

5.3. Neural Network Analysis

Artificial Neural Networks (ANNs) operate through a layered architecture, incorporating an input layer, neurons within hidden layers, and an output layer. In the context of assessing the impact of Responsiveness (RS) and Accuracy and Reliability (AR) on the overall effectiveness of AI in higher education, RS and AR act as input features. The model's neurons and hidden layers process and learn complex relationships between these input features. During the training phase, the ANN adjusts weights and biases using optimization algorithms like back-propagation to optimize the mapping of RS and AR to the dependent variable, Overall Effectiveness (OE). The ANN's ability to adapt and capture nuanced patterns in data allows it to provide insights into the interconnected dynamics of RS, AR, and OEAI, contributing to a holistic understanding of AI system's effectiveness in the educational context.

The Primitive model developed through R (Figure 3) with two hidden layer of 10 and 5 nodes each gives an error value of 0.71664. So to increase the efficiency and accuracy of the model Python was introduces to make the model more robust. The neural network model was defined using the Keras Sequential API. The architecture consisted of one hidden layer with 32 units and a rectified linear unit (ReLU) activation function. The input layer was configured based on the number of features in the training data, while the output layer had a single unit with a linear activation function, indicating suitability for regression tasks.

The compilation of the model involved using the mean squared error (MSE) as the loss function, employing the Adam optimizer, and assessing performance with Mean Absolute Error (MAE) as the metric. This compilation step is crucial for configuring the model for training. The model underwent training on the specified datasets for 150 epochs, monitoring its performance using validation data and employing early stopping as a best practice to improve generalization capabilities. During training and validation, both Mean Squared Error (MSE) and Mean Absolute Error (MAE) values exhibited a decreasing trend, reflecting the model's ability to minimize errors. The mean MSE and MAE for training data were 0.0411 and 0.1467, respectively, with standard deviations of 0.00097 and 0.00182. Similarly, for testing data, the mean MSE and MAE were 0.0345 and 0.1407, with standard deviations of 0.000997 and 0.0017. These results indicate a converging trend, visually depicted in Figure 4 & 5. Additionally, sensitivity analysis highlighted the relative importance of formative constructs AR was identified as the most influential, followed by RS at 100% and 68%, respectively (Table 4). The model's accuracy was further substantiated by the high R^2 value of 0.895 (Figure 6), signifying a substantial level of significance in predicting values compared to actual values.

6. Implications

The study's robust findings carry comprehensive implications for stakeholders in higher education and artificial intelligence (AI). Acknowledging the pivotal role of Accuracy and Reliability (AR) and Responsiveness (RS) in shaping Overall Effectiveness of Artificial Intelligence (OEAI), the implications span policy, practice, and future research. Policymakers and educational institutions can strategically enhance curricula by integrating AI technologies prioritizing high AR and RS, aligning with students' preferences for active learning and positioning institutions at the forefront of technological advancements. Optimal resource allocation in AI technologies, emphasizing AR and RS, becomes critical for institutions to effectively utilize AI tools and enhance overall education quality. Additionally, recognizing AI's impact on education, comprehensive training and professional development programs for educators are essential, emphasizing AR and RS for enriched learning experiences. These integrated strategies will contribute to a seamless incorporation of AI in education, fostering a technologically advanced and effective learning environment.

7. Concluding Remarks and Prospects for Future Research

In conclusion, this study underscores the significance of Accuracy and Reliability (AR) and Responsiveness (RS) in determining the Overall Effectiveness of Artificial Intelligence (OEAI) in higher education. The implications emphasize strategic curricular enhancements, optimal resource allocation in AI technologies, and comprehensive professional development for educators. Future research should explore additional determinants of OEAI, delve into the evolving effectiveness of AI in diverse educational contexts, and address the ethical implications of AI adoption. Comparative analyses across institutions and cultures will

provide a nuanced understanding of the interplay between AI and higher education. These efforts will advance our understanding of how AI can be effectively leveraged to enhance education.

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Table 1: Output of alpha analysis for AR, RS and OEAI construct

Reliability				
Constructs	alpha	rhoC	AVE	rhoA
AR	0.773	0.845	0.528	0.806
RS	0.733	0.845	0.647	0.793
OEAI	0.902	0.918	0.506	0.903

Table 2: Factor loading using PCA Varimax rotation matrix

Bootstrapped Loadings						
	Original Est.	Mean Bootsrap	Bootsrap SD	T Stat.	2.5%CI	97.5%CI
OEAI1 -> OEAI	0.708	0.708	0.043	16.595	0.615	0.78
OEAI2 -> OEAI	0.697	0.693	0.051	13.735	0.588	0.78
OEAI3 -> OEAI	0.717	0.714	0.05	14.276	0.61	0.797
OEAI4 -> OEAI	0.677	0.674	0.051	13.248	0.566	0.762

OEAI5 -> OEAI	0.732	0.731	0.038	19.471	0.652	0.798
OEAI6 -> OEAI	0.759	0.76	0.033	22.926	0.69	0.816
OEAI7 -> OEAI	0.734	0.731	0.04	18.173	0.644	0.804
OEAI8 -> OEAI	0.756	0.752	0.045	16.78	0.654	0.826
OEAI9 -> OEAI	0.686	0.684	0.049	14.073	0.578	0.771
OEAI10 -> OEAI	0.619	0.618	0.052	11.93	0.506	0.708
OEAI11 -> OEAI	0.725	0.723	0.05	14.447	0.616	0.813
AR1 -> AR	0.753	0.753	0.042	17.769	0.661	0.82
AR2 -> AR	0.773	0.771	0.041	18.815	0.679	0.841
AR3 -> AR	0.506	0.497	0.094	5.357	0.288	0.654
AR4 -> AR	0.739	0.735	0.045	16.265	0.639	0.814
AR5 -> AR	0.819	0.819	0.025	32.175	0.762	0.863
RS1 -> RS	0.831	0.827	0.044	18.935	0.743	0.89
RS2 -> RS	0.873	0.869	0.043	20.161	0.791	0.935
RS3 -> RS	0.697	0.676	0.12	5.805	0.43	0.812

Table 3: Discriminant Validity with Bootstrapped HTMT values

Bootstrapped HTMT					
	Original Est.	Bootstrap Mean	Bootstrap SD	2.5% CI	97.5% CI
AR -> RS	0.399	0.4	0.118	0.183	0.625
AR -> OEAI	0.853	0.856	0.052	0.746	0.945
RS -> OEAI	0.387	0.391	0.102	0.214	0.6

Table 4: Hypothesis Determinant Factors for Bootstrapped Structural Path

Bootstrapped Structural Path						
Hypotheses Test	Original Est.	Bootstrap Mean	Bootstrap SD	TStat.	P-Value	Result
AR -> OEAI	0.706	0.71	0.047	15.097	0.000**	Supported
RS -> OEAI	0.119	0.119	0.048	2.466	0.0142*	Supported

**Significant at p<0.01, *Significant at p<0.05

Table 5: Sensitivity analysis highlighting the relative importance of formative constructs (AR and RS)

Result of Independent Variables Importance	
Independent variables	Importance

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
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RS	0.407
AR	0.592

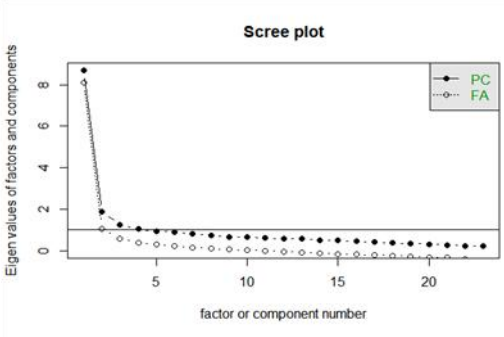


Figure1: Screen plot for AR, RS and OEAI construct

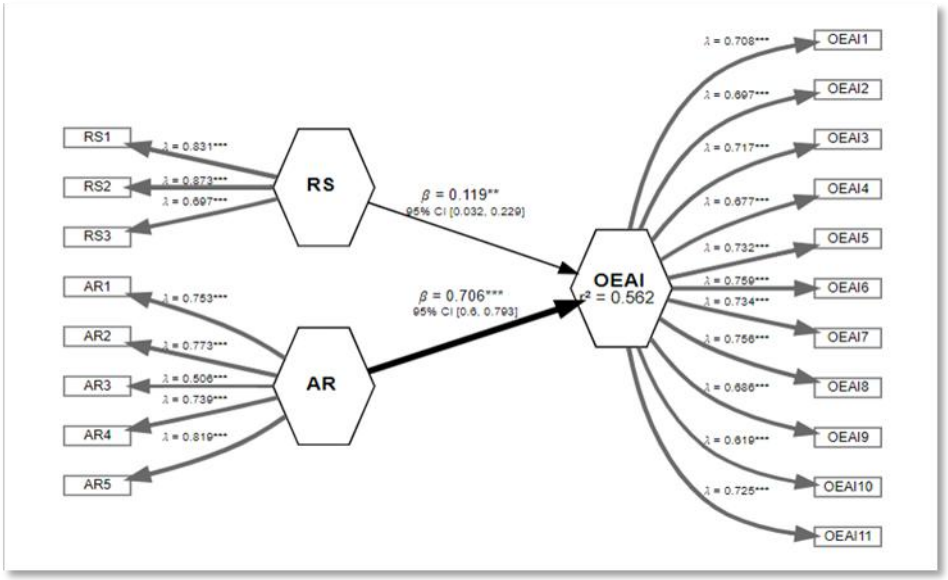
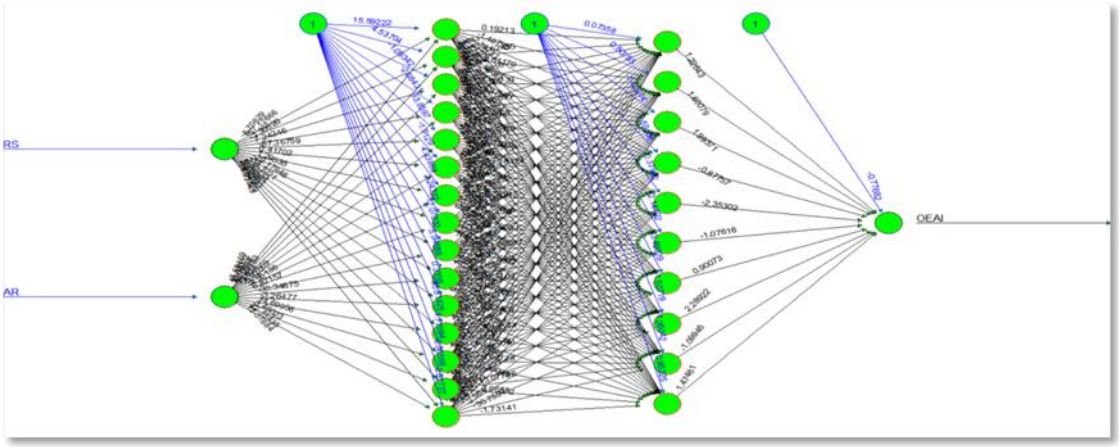


Figure 2: SEM Model for relationship Construct between AR, RS and OEAI



European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk

Figure 3: ANN Model showing interconnected dynamics of RS, AR, and OEAI

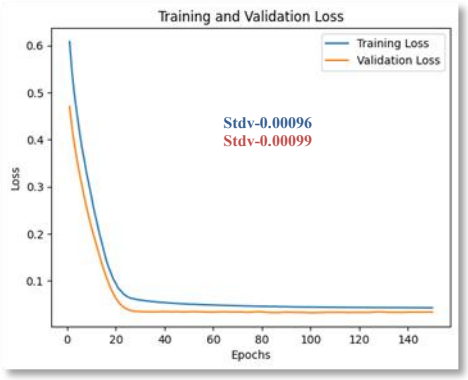


Figure 4: Mean Squared Error (MSE) and Mean Absolute Error (MAE) of training data

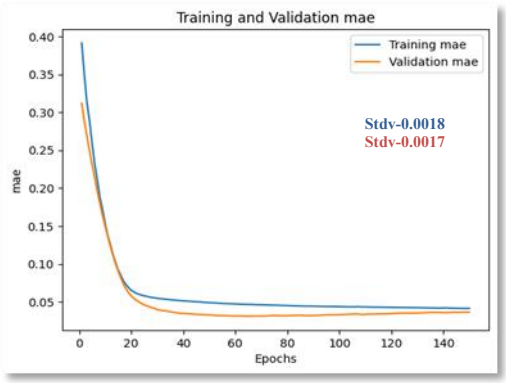


Figure 5: Converging trend of MSE and MAE for testing data

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 3 (2025)
http://eelet.org.uk

Annexure 1: The Constructs and the Questionnaire

Summary of Questionnaire		
RS	RS1	All institute classrooms are equipped for teaching with AI technology.
	RS2	My institution promotes the utilization of modern technology among its staff.
	RS3	I am satisfied with how readily available AI-related tools and technologies are in my institution.
AR	AR1	AI technology can cater the individual needs more accurately.
	AR2	AI in my institution can effectively tackle the swiftly evolving trends and demands in higher education.
	AR3	The integration of AI in higher education adequately address concerns related to student privacy and data security.
	AR4	I am optimistic about the enduring positive effects of AI on the overall educational quality in higher education institutions.
	AR5	I believe AI can enhance higher education accessibility for diverse learners.
OEAI	OEAI1	The integration of AI technology into learning activities has the capability to boost the efficiency of the higher education system.
	OEAI2	AI-generated educational content proves to be beneficial.
	OEAI3	Intelligent educational material can be created utilizing AI technology.
	OEAI4	AI technology proves valuable in facilitating educational activities.
	OEAI5	I think AI technology has the potential to be employed for responding to students' questions.
	OEAI6	I suggest that all individuals involved in higher education consider the exploration of AI technology for educational purposes.
	OEAI7	The integration of artificial intelligence into higher education yields favorable results for society.
	OEAI8	Incorporating AI into higher education holds the promise of improving the involvement and attractiveness of the teaching-learning experience.
	OEAI9	Application of AI in higher education will make the teaching-learning activity more interesting.
	OEAI10	Artificial Intelligence has the potential to enhance the personal and professional growth of students beyond their academic accomplishments.
	OEAI11	I am of the opinion that Artificial intelligence holds the capability to improve evaluation and feedback processes in higher education.