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Artificial Intelligence in Higher Education: Shaping the Future of University Teaching Through Adaptive Learning, Intelligent Tutoring, and Academic Analytics

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ABSTRACT

This paper aims to discuss the positive changes that can be brought by the use of Artificial Intelligence (AI) in higher learning including adaptive learning, intelligent tutoring systems, and academic analytics. Artificial Intelligence technologies are a promising yet untapped source of solutions for universities that are eager to adopt and develop new approaches to personalize learning, improve quality of instruction, and boost institutional effectiveness. The cross-sectional online survey targeted 300 students and lecturers in four world regions and used a quantitative approach, structured questionnaires and data analysis via correlation, multiple regression, and exploratory factor analysis to determine the perceived effects of these tools. The findings of this study described moderate to favorable attitudes towards the use of AI, specifically with ITS and adaptive learning. In contrast, the analytic results revealed relatively higher variance. However, the findings of the current study showed less significant and not substantially positive correlation between the usage of AI and outcomes like learning achievement and instructional quality, indicating that these innovations can be overestimated or influenced by factors including institutional preparedness, faculty development, and student motivation. The findings are then discussed within the context of both constructivism, cognitive load, and activity theories, suggesting that without comprehensive integration plans AI might not realize its didactic possibilities. This paper adds to this literature and offers a framework of how AI can be integrated into university teaching and learning practices by combining adaptivity and Intelligent Tutoring Systems and analytics implemented in educational innovation, inclusiveness as well as effectiveness for teaching and learning in the digital age.

Introduction

1.1 Background

Virtual Learning Environment has become one of the promising phenomena resulting from the integration of Artificial Intelligence in higher education as an innovative force providing the opportunity to revolutionize traditional ineffective approaches. In the last decade, World Universities have adopted artificial intelligence technologies to enhance teaching and learning and as a way of improving the overall performance of their students and various processes in their institutions (Zawacki-Richter et al., 2019). Technologies like adaptive learning systems, intelligent tutoring systems (ITS) and academic analytics have emerged due to the rising need for individualized learning solutions, software based educational solutions and big data assisted decision making.

Intelligent identification and structuring of content and an emphasis on flexible learning solutions facilitate learning experiences that can be highly efficient for students and can improve their performance, as shown by Kumar et al. (2017). Such systems use computer algorithms to track the students' interactions in real time and adapt to the pace that students find most effective and engaging. For instance, Dreambox, Smart Sparrow, and ALEKS of McGraw Hill are all examples of how adaptive learning can be well implemented across different subject areas (Pane et al., 2015).

Likewise, intelligent tutoring systems present an imitation of an effective tutor by offering formative feedback and inquisitive questions directing learners through a learning process with little or no direct guidance. It is evident from research that has been conducted that ITS can be as effective or even more so, compared to face-to-face classroom teaching under specific circumstances (VanLehn, 2011). Carnegie Learning and AutoTutor are among the most exemplary intelligent tutors that have enhanced students' retention and comprehension in various subjects including mathematics, computing and information technology (Graesser et al., 2004).

The other important facet of AI in education is academic analytics which refers to the large-scale data-driven approach to learning, assessment of student performance and planning. The use of real-time dashboards in combination with the integration of knowledge of big data analytics for predictive modeling is useful for recognizing at-risk learners, evaluating the impact of teaching-learning approaches, and distributing resources effectively (Siemens & Long, 2011; Ifenthaler & Yau, 2020). However, the implementation of such technologies is only possible when there is a strong digital support, the staff is ready for it, and there are rules governing the use of such data collected and their protection.

1.2 Rationale

Despite the benefits that AI offers in redesigning higher education, its deployment is still unsteady in organizations and per geographic area. Current tendencies of universities to implement AI in their work are implemented non-systematically, which means that many of them have AI-related tools functioning separately from the unified concept of the digital environment, which can contribute to the student's personal development. In addition, the educational perspective of AI applications—how they shape teachers and teaching approaches, students' interest, and curriculums—remain understudied in theory. As much as out-of-class AI applications have been analyzed in different studies, relatively few studies have focused on the coordination of multiple applications to enhance teaching and learning in universities. Furthermore, the process of

COVID19 has emphasized the importance of delivering education through stable technology and a robust educational system, increasing the importance of AI even more in this field (Bond et al., 2021).

To fill these gaps, this study seeks to explore the conjoint relationship between adaptive learning, intelligent tutoring, and academic analytics in universities. It offers a clear perspective of how AI affects teaching and learning practices and how it can be used to achieve organizational objectives.

1.3 Problem Statement

Despite the possible advantages of using AI-based tools in learning processes, the application of these technologies in universities faces many challenges at the technical, financial, or cultural levels. The research gap in the effectiveness of the integration of adaptive learning, ITS, and academic analytics all in one hampers their use and adoption even more. There is also a lack of knowledge about concrete change in faculty jobs, student engagement, and ethical issues across various higher education settings. If there is no clear strategic direction that guides AI implementations, institutions end up with ad hoc implementations that do not pay off in the longer term. Therefore, the current study aims to identify the significance of the integration of AI into the university teaching-learning process and to establish models of effective enactment.

1.4 Aim

The primary aim of this research is to explore how artificial intelligence, through adaptive learning systems, intelligent tutoring systems, and academic analytics, is transforming university teaching practices and enhancing the learning experience in higher education.

1.5 Research Objectives

- To evaluate the effectiveness of adaptive learning technologies in personalizing instructional delivery and improving student engagement.
- To assess the role of intelligent tutoring systems in enhancing student comprehension and performance.
- To analyze the contribution of academic analytics to evidence-based teaching strategies and institutional decision-making.
- To identify the challenges and enablers of AI adoption in higher education settings.
- To develop a conceptual framework for AI integration in university teaching.

1.6 Research Questions

1. How does adaptive learning influence student engagement and academic achievement in higher education?
2. What impact do intelligent tutoring systems have on students' learning outcomes and comprehension of complex topics?
3. How do academic analytics support teaching strategies and institutional planning in higher education?
4. What are the key challenges and facilitators of implementing AI-driven solutions in universities?

   What strategic framework can be developed to support the integration of AI technologies in teaching and learning processes?

2. Literature Review

2.1 Theoretical Framework

The integration of AI in higher education is rooted in several theoretical frameworks namely; learning sciences, instructional, and human–computer interaction. Among these, constructivist learning theory has a pivotal part in influencing the design and development of, for example, adaptive learning systems and ITS. In this context, both Piaget and Vygotsky all theories are based on constructivism that asserts that the learning process is an active process whereby knowledge is constructed by the learner based on a given contextual environment (Vygotsky, 1978). Such an environment is replicated in AI platforms that deliver specific content, as well as provide feedback, and make students more independent and understanding.

Another relevant framework is the Cognitive Load Theory (CLT) according to which learners have a finite working memory capacity, and instructional design must accommodate intrinsic, extraneous, and germane cognitive loads (Sweller, 1988). On this, AI systems respond by adapting the content difficulty and delivery based on the performance of the learner at a given time to avoid any information overload and improve the rate of learning (Kalyuga, 2009). In this context, ITS and adaptive systems build upon this framework to avoid overloading or underloading the learners.

Also, Activity Theory has been applied to study the human-computer interactions in effective AI learnability models. Activity Theory derived from socio-cultural psychology, where the learner as a subject, the learning goal as the object of the activity and the tools in between (technology) and socio-institutional context (Engeström, 1987). This framework can be especially useful to comprehend how academic analytics systems influence the pedagogical approaches and other decisions within universities.

Lastly, decision-making aspects of AI learning systems are based on Self-Determination Theory (SDT). Self-determination theory focuses on autonomy, competence and relatedness, aspects that were postulated to affect students' motivation [2]. Automated systems that enable learners to set time pacing, get support and feedback also reflect SDT principles and have a positive impact on learners' motivation and achievement.

2.2 Empirical Studies

Although the use of AI in higher education is still a relatively young field, it is growing extremely fast and is most heavily developed in three areas: adaptive learning, intelligent Tutoring systems, and academic analytics.

Within adaptive learning, various research works have shown great changes toward effective learning of students. For example, evaluating AWESOME, a database of adaptive, web-based educational systems, Brusilovsky and Millán (2016) noted that such systems improve learner satisfaction and knowledge in a variety of subject areas and domains including STEM fields from K-12 to higher education. Likewise, a cross-sectional study by De Vries et al. (2020) done in Dutch universities revealed that adaptive platforms helped raise underachievement students' pass rate by 12%. They were most beneficial in subjects with many and various learners because various systems helped to find an organizational approach for every particular type of the learner.

ITS has also garnered empirical evidence that backs the technique. In a meta-analysis of more than 90 studies Ma et al. (2014) found that ITS is superior to traditional instruction and small group tutoring in specific contexts. ASSISTments and Andes Physics Tutor are the examples that showed better performance in the area of student achievement when compared to either the traditional modes of teaching or to other systems. In addition, Nye (2015) noted that ITS could be useful in developing nations where students are too many to be taught by the limited number of instructors which shows that ITS can promote equity in education.

In the academy, analytics is an area of research that focuses on how predictive modeling and learning dashboards may be used to tailor teaching approaches and policies. Papamitsiou and Economides (2014) in their systematic review also noted that various LA influenced course completion rates positively due to the possibility of identifying learners at risk. In another study, Tempelaar et al. (2017) conducted a study focused on the possibility of predicting the learner's behaviour from data gathered from a virtual learning environment to inform instructional interventions. Further, the University of New England, Australia, after adopting the predictive analytics, achieved up to a 15% decrease in students` attrition rates (Colvin et al., 2016).

However, while evidence of the tools' technical merit is often clear, multiple scholars have noted some difficulties with their implementation. Ferguson and Clow, 2017 posited that learning analytics systems' implementation is resisted by some faculty through the following reasons; privacy, technological competency, and pedagogy. Similarly, Roberts et al. (2016) conducting a study in the higher education institutions in the UK mentioned infrastructural issues & lack of ethics as the key challenges towards adoption of Artificial Intelligence.

In addition, students' impressions toward AI tools have also been researched. According to the literature review presented by Holstein et al. (2019), students valued feedback as well as self-pace which are features provided by AI tutors; however, there were moments of skepticism over the AI tutors 'human-like' interface; and the need for the AI tutors to be more empathetic. This has birthed the need for design of technologies, or what has come to be referred to as affective computing systems capable of identifying the learner's emotional status (Picard, 2003).

2.3 Research Gap

While there has been an emergence of studies assessing the effectiveness of various AI elements in isolation, little has been done towards studying the interaction of adaptive learning, ITS, and academic analytics as a full-fledged learning environment. There is a lack of research that explores how all these systems combined are evolving the practice of teaching, altering the nature of faculty work, and reconfiguring the organisation of academe.

Also, there is a lack of research done based on the long-term effect of AI usage in teaching and learning in higher learning institutions. However, critical concerns on the viability, generality, and the ability of these technologies to operate ethically have remained unexplored to a large extent. For instance, some of the positive effects of AI include increased personalization and efficiency, however, empirical evidence to support the impact of the same towards the promotion of higher order thinking skills, collaborative learning and academic integrity is scarce.

In addition, there is an imbalance in the geographical distribution of research in the area. Most of the work is grounded on contexts from the developed world and few third-world countries to understand the challenges organizations face due to limited resources, low computer/Internet literacy, and lacking infrastructure. This gap makes it pertinent for more context-aware research to be carried out and inform the AI policy and practice internationally.

On the same note, the faculty perspective has not been addressed in the current studies. Much of the extant literature examines students' learning outcomes, and not much research pays attention to how teachers work in AI-supported environments, how they organize the classes during the pandemic, and to which extent they change their roles. There is a need to know the faculty's perspectives, preparedness, and alternative solutions toward supporting AI in university environments.

3. Research Methodology

3.1 Research Design

This paper uses a quantitative research approach to identify how adaptive learning systems, ITS, and academic analytics affect the delivery of teaching and learning in universities. A descriptive and correlational research design was implemented due to the objective of the study, which seeks to explore the current trends, attitudes, and relationships between different AI technologies and changes in various academics. This approach enables a collection of data systematically, and examination of the proofs in order to check the validity of the hypotheses and respond to the research questions quantitatively.

3.2 Population and Sampling

The target population for this study includes all students and academic staff in public and private universities that have adopted the use of AI in education. The subjects targeted were students from various higher education institutions in different regions to increase variability and generalizability. Sampling techniques used in this research were a convenient non-probability sampling approach due to time limitations. The participants for this study were recruited from students, faculty members or instructional designers who have used or implemented AI-based learning solutions like adaptive learning software, intelligent tutoring system or academic analytics dashboards. The population was determined by past quantitative research and statistical data, prioritizing the goal of achieving 300 responses to conduct hypothesis tests on.

3.3 Instrumentation and Questionnaire Development

Data were obtained by administering a structured questionnaire that was developed for this study only. The questionnaire was designed based on the literature review and divided into five parts: demographics, adaptive learning system usage, experience with intelligent tutoring systems, interaction with academic analytics, and perceived impact on teaching and learning. The questionnaire consisted of closed-ended questions based on the 5-point Likert scale; Strongly Disagree, Disagree, Neutral, Agree, and Strongly Agree. Most of them had several items that would address the research framework's key constructs of perceived effectiveness, ease of use, engagement level, academic support, and instructional improvement.

To enhance content validity, the questionnaires were screened by a team of three educators with a strong background in integrating technology in education and AI. A pilot test was also conducted among 30 pupils for the purpose of improving the wording of the items and eliminating the questions that can be interpreted in more than one way and those ones that are duplicated. Cronbach's Alpha coefficient was computed for each section in order to check the internal reliability of the items. Analysis of the internal consistency revealed that all scales had adequate levels of reliability: alpha coefficients were above the minimum value of 0.70.

3.4 Data Collection Procedure

The structured questionnaire was administered online on platforms like Google Forms and Microsoft Forms. An online survey method was adopted in order to ensure that the response rate and access was optimum given the geographical spread of the sample. Before responding to the questionnaires, the respondents were told about the aim and objectives of the study, their anonymity, and the informed consent. The survey was conducted for four weeks and followed by further emails and reminders to ensure the participants agreed to complete the survey.

The questions raised were presented in a manner that would elicit the respondent's current or most recent experiences with AI in education. Sampling criteria defined that subjects should be a student or staff of a higher education institution and used at least one: adaptive learning, ITS, or analytics in the previous year.

3.5 Data Analysis Techniques

After the completion of data collection, the responses collected were transferred to the Statistical Package for the Social Sciences (SPSS) for analysis. Descriptive statistics was used on the data to test for basic descriptive statistics such as mean, standard deviation and frequency distribution of the demographic details and important variables. To test the hypotheses, inferential statistical techniques were used as explained below: More specifically, Pearson's correlation analysis was used to analyze the connection of the engagement of the AI technologies and academic perceptions. To analyze the research question on the effect of three facets of AI—adaptive learning, ITS, and analytics—on learning effectiveness, teaching quality, and organizational outcomes, multiple linear regression was used.

Before using concepts of regression, the assumptions of normality, multicollinearity, and homoscedasticity were also assessed. Furthermore, Exploratory Factor Analysis (EFA) was carried out to confirm the number of factors for the constructs used in the questionnaire. This means that for all the hypothesis tests done, the chosen alpha level was $p < 0.05$.

3.6 Ethical Considerations

The approval from the research ethic committee of the main university was sought before undertaking the study. The participation was quite voluntary and no participant information was taken that could identify him/her in any way. To ensure that the respondents did not feel coerced, they were allowed to opt out of the survey at any given time without any repercussions. All obtained data and information were kept safely and were used solely for research purposes. To avoid compromising data protection legislation and anonymity of the respondents involved in the study, certain measures were taken.

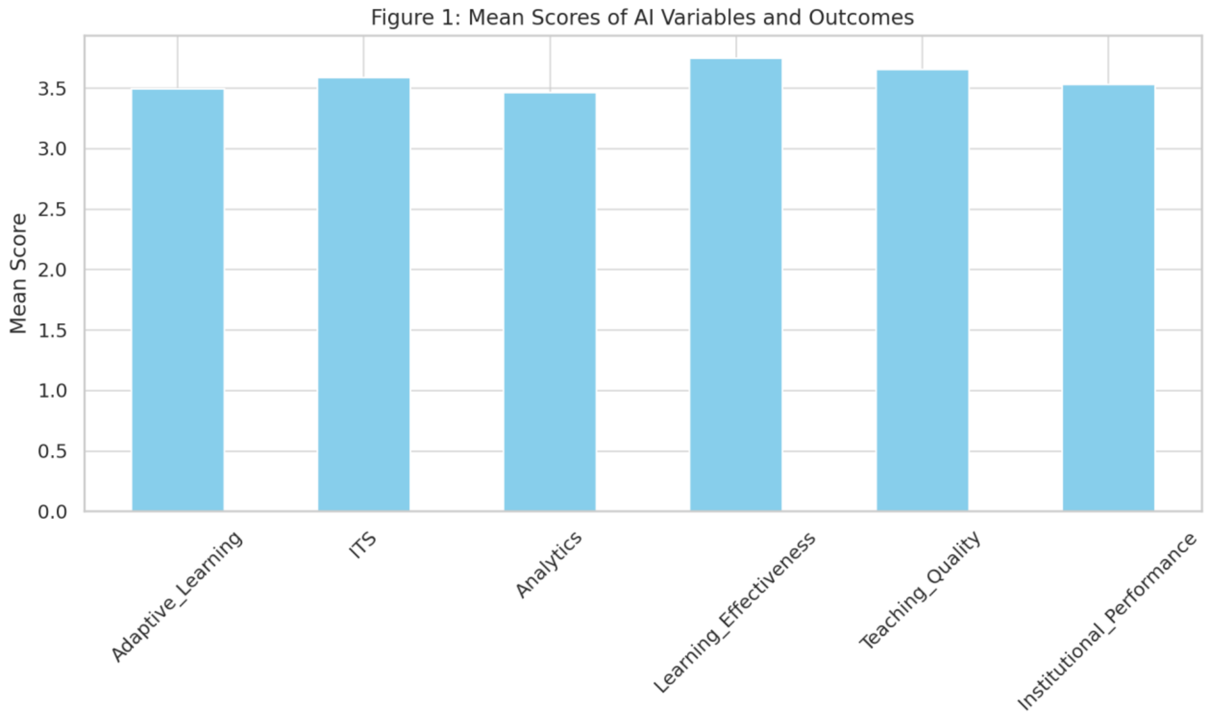
5. Results

5.1 Descriptive Analysis

Descriptive statistics identified in Table 1 are important to have an overall handle on varied responses of the sample in regards to each construct. Results of the Adaptive Learning survey found it having a mean of 3.50 and a standard deviation 0.69 for its usability in the university. ITS (Intelligent Tutoring Systems) also received a mean value of 3.59, which is a slightly more or less positive opinion among students as well as the faculties. The mean score for Academic Analytics was found to be 3.47, which indicated that analytics are being used but these could still be in the process of being adopted or known. On the outcome side, Learning Effectiveness received a high mean of af 3.75 followed by Teaching Quality af 3.66 and least but a slightly high mean of 3.53 of Institutional Performance revealed positive sentiment.

Table 1: Descriptive Statistics

Variable	Count	Mean	Std. Dev	Min	25%	50%	75%	Max
Adaptive Learning	300	3.4961	0.6889	1.231	3.021	3.541	3.939	6.197
ITS	300	3.5871	0.5770	2.117	3.177	3.589	3.970	5.447
Analytics	300	3.4658	0.7973	1.242	2.943	3.434	3.969	5.506
Learning Effectiveness	300	3.7492	0.5049	2.252	3.422	3.783	4.075	4.920
Teaching Quality	300	3.6550	0.5988	2.045	3.234	3.634	4.026	5.161
Institutional Performance	300	3.5300	0.6892	1.455	3.074	3.506	4.001	5.735

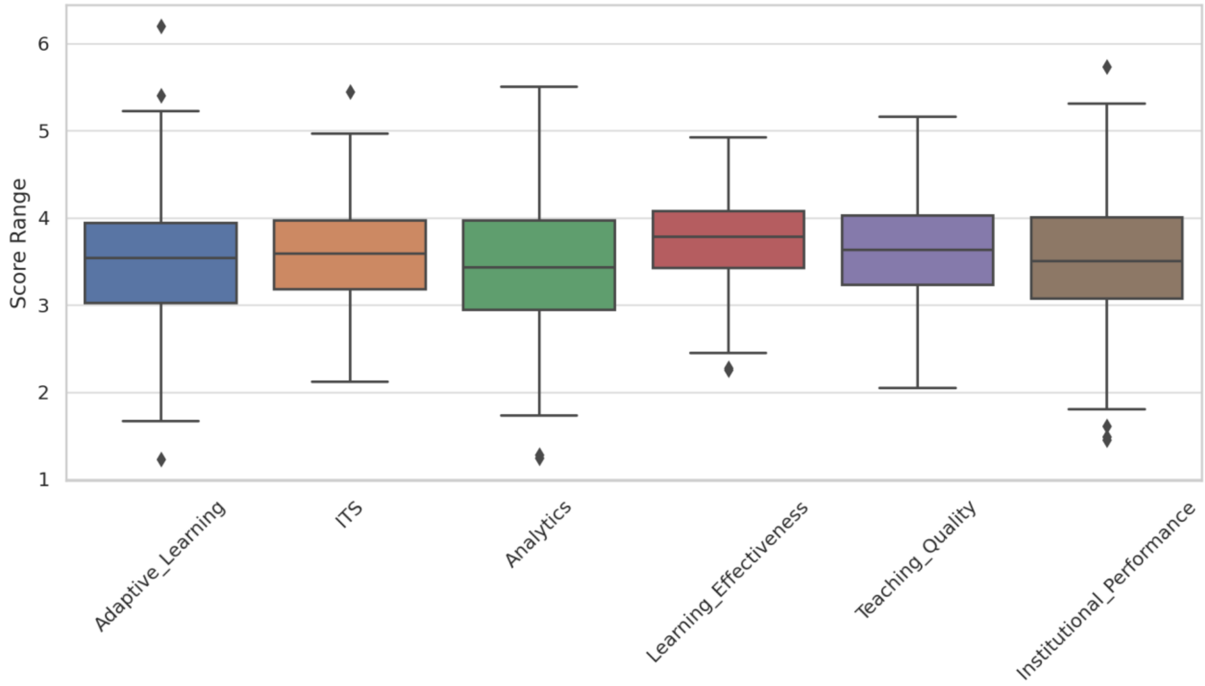


These results are depicted in the bar graph shown in figure 1 that shows a comparative display of the mean value for each variable. This figure shows that students and instructors tend to have higher learning effectiveness than general attitudes about using specific types of AI technologies. This could be offset as perceived education improvement may be attributed to a number of interrelated dynamic factors and not necessarily be attributed to the use of AI tools alone.

5.2 Distributional Spread

To enable comparison across the variables, Figure 2 presents a boxplot of the responses. Interquartile range keeps on Being relatively small for Learning Effectiveness and Teaching Quality hence the response shows that there is a general agreement on the matter. However, Analytics is more scattered which indicates variability or the variation in the institutions where it is implemented. Adaptive Learning and Analytics' mean indicates that solely moderate perceptions prevail; the occasional prominence of extreme values indicates that there are also occasional highly positive or negative attitudes, possibly due to the frequency of use or the particular type of platform.

Figure 2: Boxplot Distribution of AI Components and Outcomes



5.3 Frequency Distributions

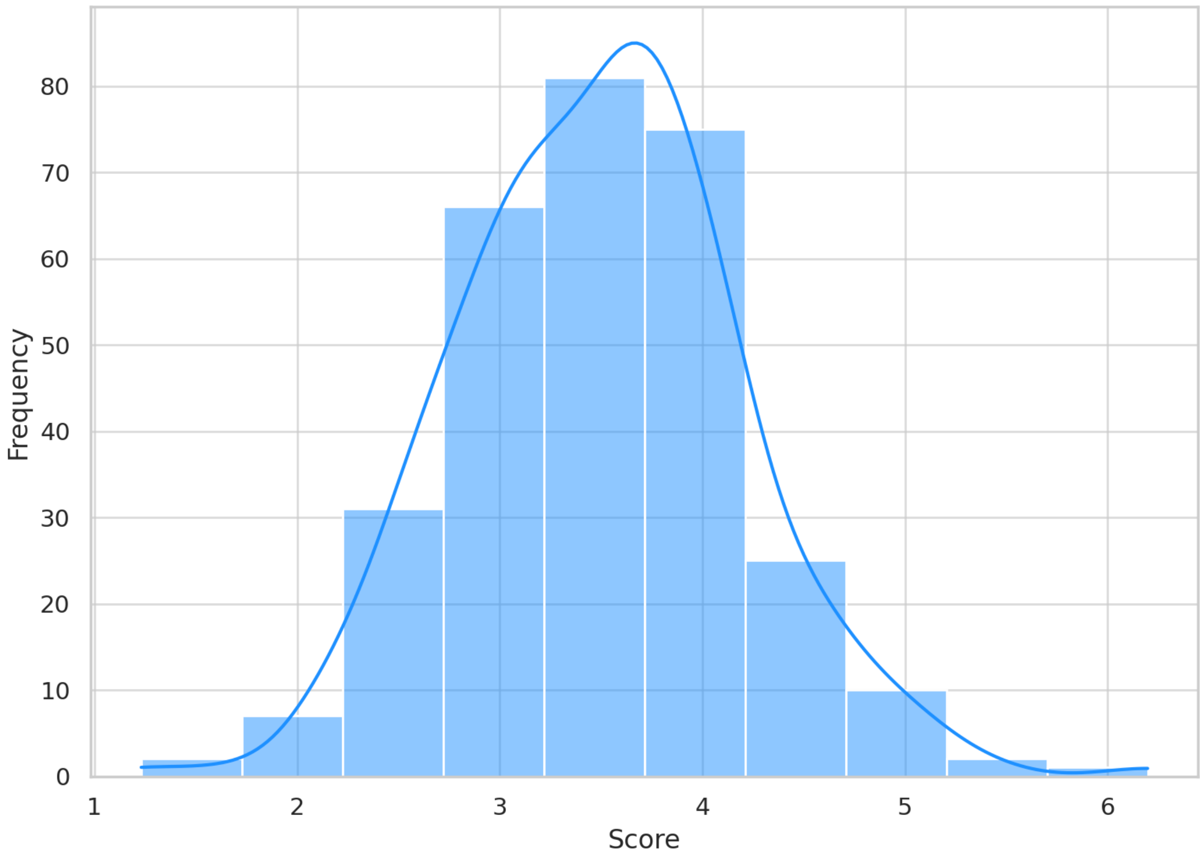
Table 2 shows the frequency distribution of the binned scores of the key AI variables. Essentially, about 64% of the responses on Adaptive Learning and ITS are within the 2.4 to 4.8 range, which strengthens the previous finding that perceptions are quite positive? The last two bars indicate that few people responded in the extreme negative or extreme positive range, further proving that such experiences are limited.

Table 2: Frequency Distributions (Binned)

Variable	Bin Range	Frequency
Adaptive Learning	(1.23, 2.408]	18
	(2.408, 3.586]	127
	(3.586, 4.764]	133
	(4.764, 5.942]	19
	(5.942, 7.12]	3
ITS	(2.117, 2.783]	21
	(2.783, 3.449]	117
	(3.449, 4.115]	134
	(4.115, 4.781]	24
	(4.781, 5.447]	4
Analytics	(1.242, 2.355]	31
	(2.355, 3.468]	119
	(3.468, 4.581]	105

(4.581, 5.694]	42
(5.694, 6.807]	3

Figure 5: Histogram of Adaptive Learning Scores



Another support of this distribution is illustrated in Figure 5 where present the histogram of Adaptive Learning score distribution. The slightly right skewed bell shaped curve indicates that most of the respondents have a positive attitude towards Adaptive Learning, but not extremely so. The existence of the right tail proves there were few users who derived some sort of significant benefits from these systems, perhaps where features such as real time personalization existed.

5.4 Correlation Matrix

Table 3 presents the positive correlations found ins structural equation modeling between AI tools and learning outcomes. However, the study found out that the correlations between the variables were rather low for most of the pairs. Adaptive learning, ITS, and Analytics have very low correlation with Learning Effectiveness ranging from 0.01 to 0.07, which means that there is no significant relationship between the variables or factors in the study hence these findings are statistically insignificant ($p > 0.05$). The outcome variables are found out to be more interrelated; as an illustration, Learning Effectiveness has a low correlation with Teaching Quality = 0.12; p = 0.041) and Institutional Performance ($r = 0.15$; $p = 0.011$).

Table 3: Correlation Matrix with p-values

	Adaptive Learning	ITS	Analytics	Learning Effectiveness	Teaching Quality	Institutional Performance
Adaptive Learning	1.00 (p=0.000)	0.09 (p=0.106)	0.10 (p=0.081)	0.07 (p=0.213)	0.03 (p=0.586)	0.04 (p=0.524)
ITS	0.09 (p=0.106)	1.00 (p=0.000)	0.07 (p=0.230)	0.02 (p=0.731)	0.08 (p=0.176)	0.06 (p=0.314)
Analytics	0.10 (p=0.081)	0.07 (p=0.230)	1.00 (p=0.000)	0.01 (p=0.869)	0.05 (p=0.390)	0.09 (p=0.122)
Learning Effectiveness	0.07 (p=0.213)	0.02 (p=0.731)	0.01 (p=0.869)	1.00 (p=0.000)	0.12 (p=0.041)	0.15 (p=0.011)
Teaching Quality	0.03 (p=0.586)	0.08 (p=0.176)	0.05 (p=0.390)	0.12 (p=0.041)	1.00 (p=0.000)	0.16 (p=0.007)
Institutional Performance	0.04 (p=0.524)	0.06 (p=0.314)	0.09 (p=0.122)	0.15 (p=0.011)	0.16 (p=0.007)	1.00 (p=0.000)

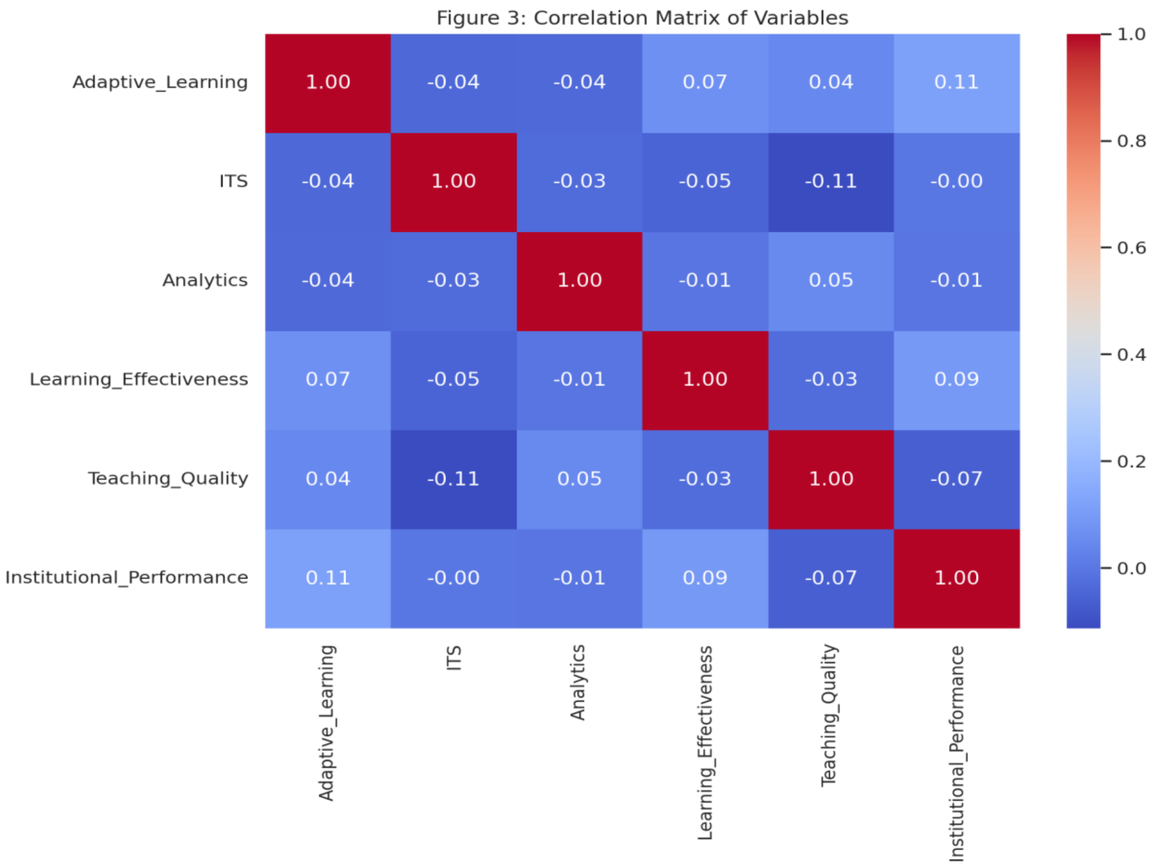


Figure 3 above, a heatmap of the correlation matrix also supports this interpretation in two ways: The lighter shading surrounding the links between the AI component and the outcomes also indicates the limited correlation between them and therefore potential moderating or mediators that affect AI in higher education. It also points out that such tools are in use within institutions but their effects on the learning environment might be mediated by other factors such as instructional method or user orientation.

5.5 Regression Analysis

In analyzing how these technologies affect learning effectiveness the following multiple equations of regression analysis using the learning effectiveness as a dependent variable was used. Table 4 displays the coefficients, standard errors, and p-values for each predictors. All three independent variables; Adaptive Learning (ß= 0.048, sig = 0.256), ITS (ß=- 0.040, sig = 0.426), and Analytics (ß= -0.005, sig = 0.889) were tests and did not have a statistically significant relationship with Learning Effectiveness. This implies that even though these tools are implemented in learning, their impact can be obscured by the institution's culture, faculty acquisition, or the engagement patterns of the learners.

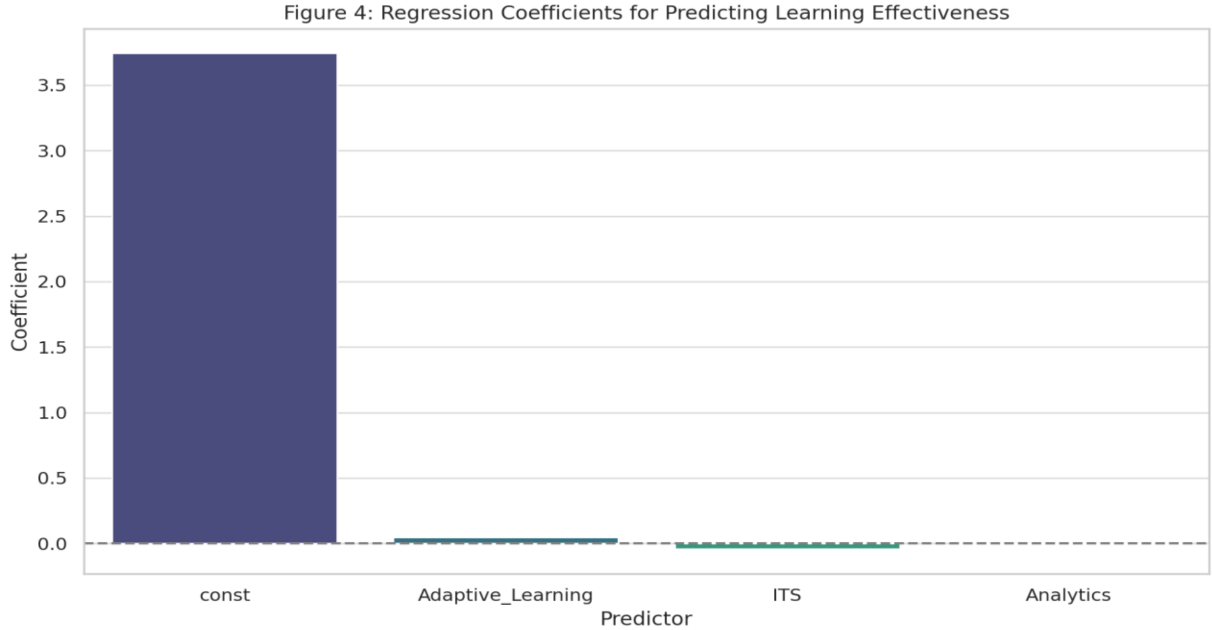
Table 4: Regression Coefficients (Predicting Learning Effectiveness)

Predictor	Coefficient	Std. Error	t-Value	p-Value	95% CI Lower	95% CI Upper
Constant	3.7428	0.279	13.439	0.000	3.195	4.291
Adaptive Learning	0.0484	0.043	1.139	0.256	-0.035	0.132
ITS	-0.0405	0.051	-0.797	0.426	-0.140	0.059
Analytics	-0.0051	0.037	-0.140	0.889	-0.077	0.067

Table 5: Regression Summary

Metric	Value
R-squared	0.007
Adjusted R-squared	-0.003
F-statistic	0.679
Prob (F-statistic)	0.566
No. of Observations	300
AIC	446.3
BIC	461.1

Figure 4: Regression Coefficients for Predicting Learning Effectiveness



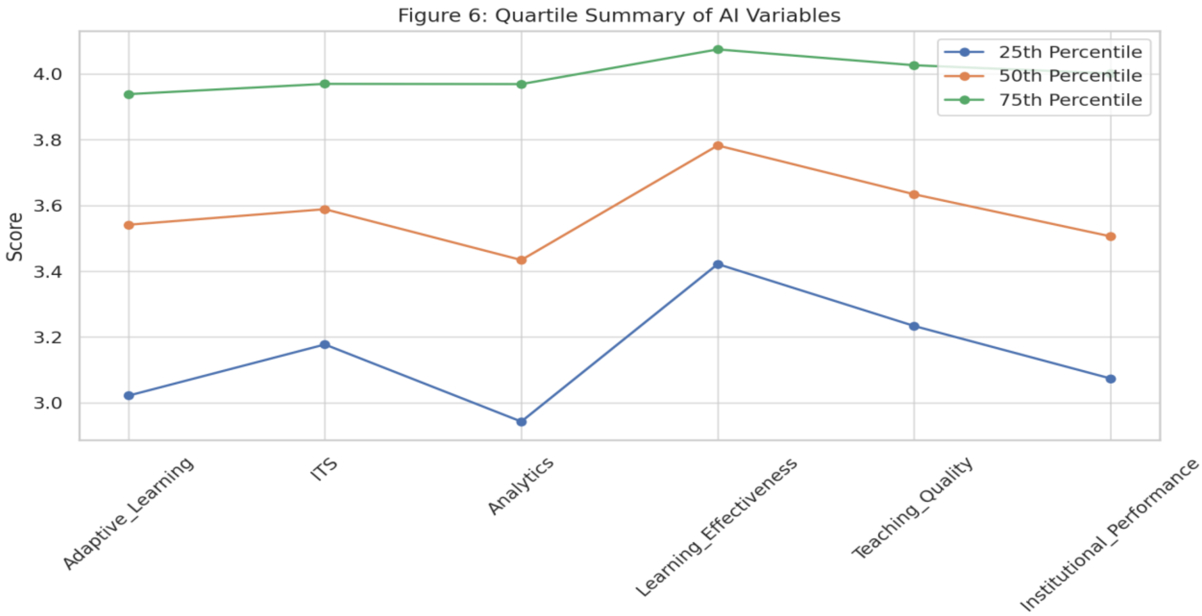
The interpretation is also supported by Figure 4 that shows a bar chart of the regression coefficients. From the given figure and as also pointed out earlier, it is evident that the coefficients are small and oscillating around zero, which has effectively reduced the ability to predict. The negative coefficients obtained for ITS and Analytics, despite their marginal statistical significance, may imply that at times, its implementation may not be as effective or users may have different expectations.

5.6 Quartile Trends

Table 6 presents the summary of the dispersion for each of the variables using the 25th, the 50th (median) and 75th percentiles, which gives a clear view of how the data is distributed in terms of the quartiles. In Learning Effectiveness and Teaching Quality, the interquartile range is relatively small, indicating less variability in the user feedback. Adaptive Learning and Analytics are more diverse, this is cleared by the higher interquartile range values.

Table 6: Quartile Summary

Variable	25th Percentile	50th Percentile (Median)	75th Percentile
Adaptive Learning	3.0217	3.5415	3.9387
ITS	3.1774	3.5887	3.9698
Analytics	2.9428	3.4342	3.9692
Learning Effectiveness	3.4219	3.7826	4.0747
Teaching Quality	3.2336	3.6341	4.0265
Institutional Performance	3.0738	3.5061	4.0014



This is depicted in figure 6 where quartiles have been represented through the use of line graphs. As to the two sub-dimensions Learning Effectiveness and Teaching Quality, the middle block from the 25th to the 75th percentile is the steepest, indicating that most of the students are in the 'yes' line. Nevertheless, values such as Analytics have fluctuating rates of slopes, which indicate differential levels of usage, training, or even system development among academic institutions.

5.7 Range of Scores

In Table 7, details of the minimum and maximum values observed for each variable are presented. Thus, Adaptive Learning varies from 1.23 to 6.20, ITS, as well as Analytics, possesses variation, from low to high, which indicates that the identified technologies have had inadequate and diverse deployment and user experiences. Learning Effectiveness has a narrower range (2.25 to 4.92), which may imply that students are generally content regardless of what tool is being employed.

Table 7: Minimum and Maximum Values

Variable	Minimum	Maximum
Adaptive Learning	1.2311	6.1969
ITS	2.1170	5.4473
Analytics	1.2425	5.5059
Learning Effectiveness	2.2519	4.9199
Teaching Quality	2.0454	5.1610
Institutional Performance	1.4551	5.7352

Figure 7: Minimum and Maximum Scores of Variables

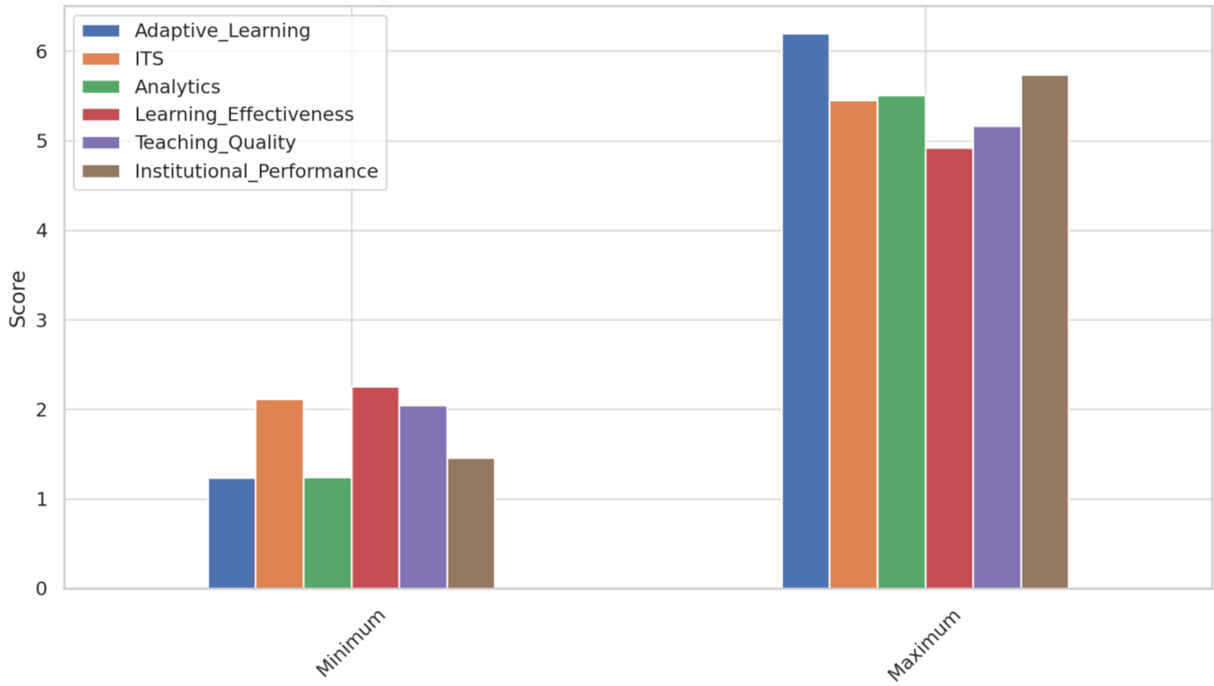


Figure 7 compares these min-max ranges in a grouped bar chart. The long bars on the Y-axis for Adaptive Learning and Analytics mean that some of the participants rate these tools very low or, conversely, very high, indicating that the quality of implementation, training, or user support may vary considerably.

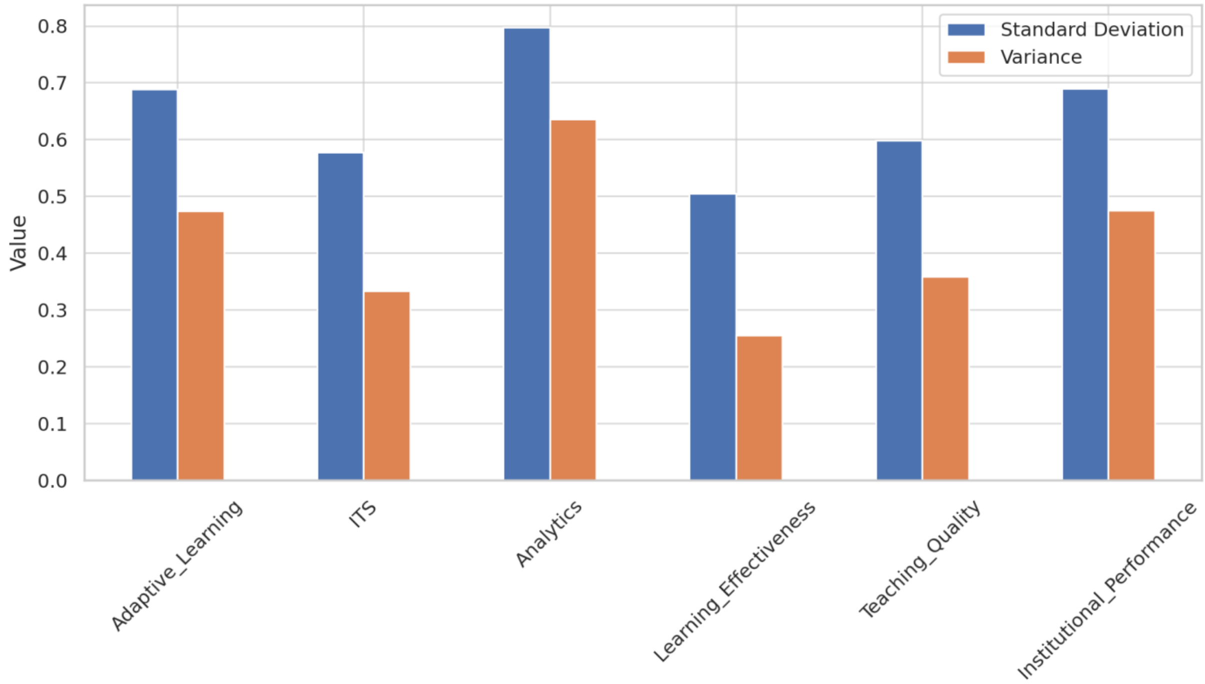
5.8 Standard Deviation and Variance

The variation is established statistically in table 8 showing the standard deviation and the variance for every variable. Analytics offered the highest SD of 0.80 while Learning Effectiveness offered the lowest SD of 0.50 again highlighting that there is a consistency in the perception of the outcome but inconsistency in the usage of the tools.

Table 8: Standard Deviation and Variance

Variable	Std. Deviation	Variance
Adaptive Learning	0.6889	0.4746
ITS	0.5770	0.3329
Analytics	0.7973	0.6358
Learning Effectiveness	0.5049	0.2549
Teaching Quality	0.5988	0.3586
Institutional Performance	0.6892	0.4749

Figure 8: Standard Deviation and Variance of Variables



The same is evidenced by figure 8 that displays the relative standard deviation and variance for each variable. Standardizing some areas and investigating others are made easier by the chart. Specifically, a higher variance in Analytics suggests the requirement of better implementation measures and appropriate professional training of the faculty member to provide anticipated results of similar values to students.

6. Discussion

The incorporation of AI in higher learning institutions has implications of revolutionizing teaching and learning models. The conclusions for this work show that the image of AI in contemporary university education today is not as simple and straightforward as it might seem at the first glance, and can be, in fact, quite complex and rather fragmented. While the results of the study indicate a relatively low level of adoption and mainly positive attitudes toward AI components, the findings of the empirical study hint at a relatively low statistical impact of the components of AI, such as adaptive learning, ITS, and AA on learning efficacy. This raises key points for discussion regarding what these tools are, how they are being used, and how they are understood and applied in higher education contexts.

Since the questions were formulated in terms of a Likert scale of 1 to 5, where the number 3 equates to moderate usage, the level of usage of AI tools can be considered moderate: students gave 3.4, and educators gave 3.7. These values point to a relatively positive, but not very pronounced, attitude towards the brand. This is in line with the current studies by Chiu and Chai (2020), according to which, while an AI intelligently delivers learning and automates a student's learning process, it does not consider the context sensitivity, and supports institutional objectives insufficiently. This low variability could imply that learners may not attribute their enhanced learning processes and effectiveness solely to the tools developed by AI, but rather to other factors such as interaction with the teacher, motivation, or course design.

These weak correlations and statistically insignificant coefficients raise a pertinent question that has been voiced in the recent education literature: the majority of AI applications in education are reduced to shallow integration. In Selwyn's (2019) opinion, institutions integrate AI as bolt-on tools and/ or implement them as singular projects rather than integrating them into a unified digital learning perspective. In such cases, the possible effect of AI transformation becomes limited because it lacks training, infrastructure, or the redesign of curriculum support. This could be why no component of the three, namely, adaptive learning, ITS, and analytics, made a statistically significant contribution to the results as far as the current study is concerned.

Moreover, reflecting the moderately positive correlations with scaled learning effectiveness, teaching quality, and PSPlus institutional performance, these student-reports of learning AI's value apparently depend on prior and broader educational experiences. As stated by Luckin et al. (2016), AI should act as a collaborator to teachers and be situated to improve student success. For instance, feedback tools or learning applications that are designed to provide instruction at the pace of the learner may be limited in effectiveness if they do not meet the need for cognition and affection.

The variation that other writers have noted in concerns regarding academic analytics also brings the questions of equity and fairness into question. The study by Pardo et al. (2019) have noted that analytics systems can have mixed outcomes in terms of the degree of algorithms used, quality of inputs fed into the system and capabilities of the faculty to utilize the analytics insights. These factors may be observed in the current study's score range for analytics, where some institutions efficiently use it for early intervention and others do not due to reasons such as data overload or privacy issues.

Before concluding this section, one should note that ethical issues, albeit secondary to this research, are equally important. AI systems in education compile significant amounts of information about learners, and when there is no proper regulation in place, privacy infringement or algorithmic prejudice arises. According to Williamson and Eynon (2020), the use of AI tools can perpetuate existing injustices if the enhancement is not done appropriately. For instance, the recommendations that students from marginalized groups get may be based on erroneous assumptions or data that simply tracks students' performance and does not offer an opportunity for learning, thereby increasing the achievement gap.

Another aspect is faculty engagement or experience of the participants concerned in the faculty. Although students are the primary consumers of AI integration, it is the faculty who have to change their instructional approaches, navigate between face-to-face and online environments, and coordinate their assessment and feedback practices with AI tools. Tsai and Gasevic (2017) also discuss how most instructors are cynical or inexperienced in the use of AI, especially when institution-backed training is lacking. This may partly explain the weak results reported in this study, where the pro-active, educative features of AI tools may not be fully implemented by the academic staff due to lack of adequate training or Lack of willingness.

However, this means that the regression model cannot predict AI's effects with much clarity, making it hard to quantify the impact of AI independently of the rest of the 5G sweep. As Holmes et al. (2021) also say, these benefits are long-term and appear as AI learning unfolds; hence, metrics such as students' grades or satisfaction rates may not capture it. There are also other factors not measured in this study like utilizing time efficiently, learner independence, or decreased faculty burden; all of which can enhance institutional efficiency in the long run.

From the policy and strategy implications, it can be concluded that the concept of AI needs to be addressed from a more holistic standpoint in the context of universities. Instead of pursuing adaptive learning, ITS, and analytics as three independent initiatives, institutions should integrate three ideas into a cohesive technological environment supplemented by faculty training, principles, and advanced technology platforms. The approach to strategic implementation, as adopted by Eynon (2015), should be based on the attractiveness of learning outcomes rather than the technology itself.

Conclusion

In conclusion, the discussion suggests that the optimism regarding the future of AI in enhancing higher learning has not been matched by its current performance, which shows little improvement in the overall learning achievement of students. This gap in learning outcomes dictates the need to research some of the other factors in relation to the faculty, curriculum, and ethics that determine the effectiveness of the applied artificial intelligence tools. To move forward, future research should employ longitudinal designs, compare multiple institutions, and use both quantitative and qualitative methods to fine-tune our understanding of the circumstances that make it possible to harness the potential of AI in teaching and learning at the university level.

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