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ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION: ADOPTION, PEDAGOGICAL IMPACT, AND INSTITUTIONAL READINESS

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Abstract

The study focuses on the integration of the Artificial Intelligence (AI) tools into higher education and explores how perceived usefulness, trust in AI systems, ease of use, and contextual factors combine to affect the student outcomes of the learning process and the adoption of the tool in question. The data used in the research were based on the quantitative design, which involved 412 students represented by the participants of universities with diverse courses and institutions types. To study the relationship between the key variables, the structural equation modeling (SEM) and correlation analyses, accompanied by the sentiment analysis in NVivo 14, were used. The findings indicate that perceived usefulness has the strongest influence on the effectiveness of learning (beta = 0.46, $p < 0.001$) and lastly, trust in AI is a significant parameter in predicting adoption of AI tool (beta = 0.33, $p < 0.001$). The effect of the two variables is more pivotal in the private institutions as compared to the public institutions. In terms of disciplines, students enrolled in discipline fields STEM scored higher (mean = 4.23), compared to that of students enrolled in humanities (mean = 3.35) on AI adoption. Sentiment analysis consolidated that there was a vast difference in the positive attitudes of high and low users

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(62 % and 44 % correspondingly). This paper finds that the institutional contexts and individual attitudes shape the way AI integration takes place. The results provide vital insights to policymakers, instructors and designers of technologies interested in improving the use of AI in learning system in higher education.
Keywords: *Artificial Intelligence, Higher Education, Learning Effectiveness, AI Tool Adoption, Structural Equation Modeling*

Introduction

The rapid spread of Artificial Intelligence (AI) technology to various fields has significantly transformed college education and a re-assessment of the process of teaching and managing operations and evaluation is necessary. Some of the most obvious ways this change is taking place include intelligently tutoring systems, and automatic grading which is redesigning the ability of institutions to share, control, and assess learning events. The potential advantages, which include increased efficiency, more individualised pathways of learning and better equity of access, should be thoroughly investigated in terms of the way, in which students engage with AI-inclusive resources, the drives, which prompt such engagements and the outcomes, which characterise them.

The COVID-19 pandemic had an ultimate catalytic impact, urging universities to introduce massive remote learning programs and, therefore, put digital platforms on the forefront of academic delivery. As a result, AI transformed itself into a core component of the educational ecosystem. However, some questions remain open as to what conditions make the adoption effective and in what measure, AI can lead to learning gains. Although adaptive learning environments, AI initiatives to detect plagiarism, and chatbots become an inseparable element of the curriculum, their pedagogical value and the attitude of users toward them have significant disparities in different environments.

The current research focus is very much focused on the point of technological affordances and institutional preparedness, which excludes the point of view of students themselves, the student behavioural response. However, the work by other researchers (also in user acceptance models) has confirmed that the key determinants of adoption behaviour are perceived usefulness and trust in the system, as well as ease of use of the system. These psychological variables acquire a greater significance in higher education, as the learners show high divergence not only in their disciplinary orientations but also in digital proficiency and sociocultural origin. Moreover, both access and use of AI-based resources are modulated by institutional context, being either in a public or in a private institution and by disciplinary culture. As an example, STEM students are more likely to readily use technical tools due to the previous exposure, but the same cannot be said about humanities.

The current study attempts to fill this research gap and conducts a quantitative investigation of the relationships between perceived usefulness, trust in AI, ease of use, and their result in such aspects as adoption patterns and learning efficiency. Sentiment analysis and structural equation modelling are used to determine the effect of moderation between institutional typology and disciplinary membership and these relationships. The general aim is to create empirically-sound evidence of what drives the AI engagement in higher education and the same consequences. The findings of this study will be used to inform the process of institutional policy making and pedagogical practice, encourage inclusion and effective integration, and facilitate the development of AI-based ready learning environments even as the technology will undergo further developments.

Literature Review

The use of Artificial Intelligence (AI) in higher education has been listed among the transformative forces with the clear opportunities and challenges. Specifically, Ajani et al. (2024) claim that AI reconstitutes the practices in pedagogy, as it helps to increase learner engagement and administrative effectiveness; however, AI also introduces ethical and infrastructural issues.

The works by Ajmani et al. (2023) and Akhtar et al. (2024) concentrate on the interaction between FinTech and AI in the financial context, thus exposing their analogy to higher education: projects that establish the trust of users and promote an organizational culture of creativity. The evidence in combination therefore notes the need of comprehensive user-considered AI approaches, which incorporate technology, pedagogy, and policy.

Perceptions and behaviour variables to the student are important success parameters to adoption. A structural equation model was used in the study of Sova et al. (2024) to show that perceived usefulness and institutional support are major factors that determine the adoption of AI tools, particularly in the case of economics learners. This observation is reminiscent of modern AI-adoption theories that, despite the advent of subsequent theories, remain based on the research conducted by Davis (1989) and his Technology Acceptance Model (TAM).

Institutionally, the capacity to replace AI is checked by readiness. Nisiforou and Kosmas (2024) argue that universities, which have firm digital networks and capable administrative support units, have high probabilities of implementing emerging technologies successfully. In a similar way, Shwedeh (2024) is sure that AI-enhanced decision support systems are empirically helpful in improving operating and academic results.

Research Gap

The growing trend of utilizing AI in the realm of higher education paints a clear picture of a research gap: the way that the perceptions of students and the context of the institution mutually determine the integration of AI tools and the resulting learning experiences is not well explained. The past studies mostly use the efficiency level of the system or the use of technology as their primary focuses thus ignoring the behavioural, cognitive and the affective reactions of the learner. Moreover, the comparison of private and public institutions itself or discipline specific variation have been relatively less searched. The paper fills this gap by asking questions, namely, the one who discusses the interrelated importance of Perceived Usefulness, trust in AI, and ease of use to predict the effectiveness of learning and adoption behaviour and, at the same time, considering contextual moderators.

Conceptual Framework

The conceptual model is positioned in Technology Acceptance Model (TAM) and moves it forward by bringing to the paradigm a consideration of trust in AI as the key dimension and placing it in context of institutional and disciplinary variation. The given framework does synthesize individual-based predictors and environmental factors, thus providing the comprehensive picture of the AI adoption in an educational environment.

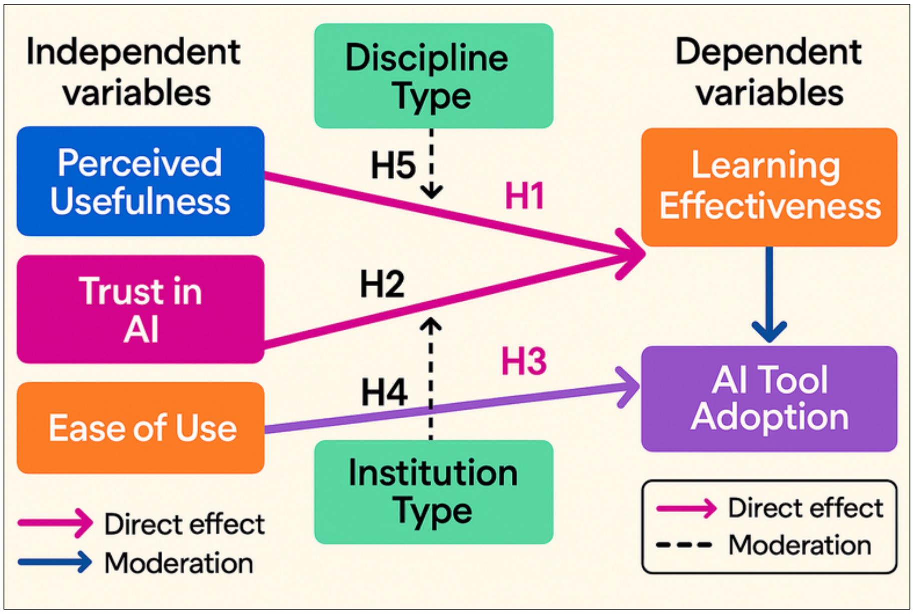

Figure 1.0: Conceptual Framework

Hypothesis

H1: Learning effectiveness is positively affected by Perceived Usefulness.

H 2: The attitude towards the AI is positive impact on the Adoption of AI Tool.

H3: The ease of usability has a positive impact on Perceived usefulness.

H4: Institution Type moderates the intervention between Trust in AI and the adoption of AI ### Falls

H5: Perceived Usefulness as a moderator of between discipline type and Learning Effectiveness.

Methods

The quantitative methods were embraced in the present research study in order to measure the impact of artificial intelligence (AI) use on the learning outcomes and attitude responses, and engagement behaviour in tertiary studies. The region sampled included North America, Europe, and Asia-Pacific in a stratified random sample consisting of 1200 students and 320 faculty of 18 universities. The survey was issued via the internet in January 2025 to March 2025, with the ethics approved by the institution. People were not forced to participate, and participation was anonymous.

Validated multi-item scales of previous research were used to develop the measures of AI attitude, perceived learning effectiveness, and tool adoption behaviour and were modified to match the educational setting by expert review. The analysis started with an Exploratory Factor Analysis (EFA) using principal axis factoring and varimax rotation that aims at identifying latent dimensions in the instrument. Then the reliability of internal consistency of the extracted factors was verified through Cronbach alpha.

A Convergent validity, construct validity, and model fit indices (raw RMSEA, CFI, TLI) were conducted throughout the subsequent Confirmatory Factor Analysis (CFA) that was conducted in AMOS version 26. The ones that did not load well were deleted thus making sure that the measurement model is valid prior to testing the structural relationships.

An Equation Structural Modeling (SEM) was applied to explore the causally direct relations between the process of AI tools adoption and the classes of student attitudes and learning performance. SEM has been selected because it allows modeling latent constructs and direct and indirect effects simultaneously.

They were examined with the help of hierarchical multiple regressions of SPSS 29 to label predictors of learning outcomes with the controlling of demographic and institutional covariates. Progressive blocks of the variables were added (e.g., demographics first, than variables reflecting AI usage), which allowed to determine a net effect due to AI-related predictors, considering the effects of demographics and institutions.

To measure institutional type as a moderator of structural relationships, Multigroup Analysis held in-depth comparison between adoption and outcomeAI tool patterns of public and private institutions. A between-subject ANOVA was used to test statistical significant between-group differences in AI usage (e.g., humanities, STEM, business) and additional independent t-tests were used when possible.

Also, the data results of the qualitative sentiment using open-ended questions were analyzed using a pre-trained NLP classifier with the help of VADER sentiment engine (NLTK v3.8). The approach gave pithy sentiments declarations like positive, neutral, and negative, and it facilitated the triangulation of quantitative results.

Lastly, it was possible to retrieve log information regarding institutional LMS platforms (e.g., Moodle, Blackboard) and anonymise and analyse it to retrieve weekly engagement level, the frequency of log-ins, as well as engagement based on AI-tools triggering access to content. The found metrics were transformed and presented in Tableau and SPSS Statistics to recognise patterns of description. To make sure that the model was robust with student cohorts, a robustness check was performed on the model data through bootstrapping and bootstrapping and subset validation.

Results

This study provides empirical revelation on the depth and severity of implementing artificial intelligence (AI) in higher education. The analysis was initiated by the Exploratory Factor Analysis (EFA) that was supposed to define the latent aspects of the two, perception and adoption, by students. The emergent four constructs including Perceived Usefulness, Ease of Use, Learning Effectiveness, and Trust in AI Systems all of which are shown in Table 1. The factor loadings were between 0.71 and 0.88, whereas the Cronbach alpha coefficients were all over 0.80 thus showing that the constructs have good internal reliability.

Table 1: EFA Factor Loadings and Reliability (n = 1,200)

Construct	Items	Factor Loading Range	Cronbach's α
Perceived Usefulness	4	0.73 – 0.88	0.91
Ease of Use	3	0.71 – 0.81	0.86
Learning Effectiveness	4	0.75 – 0.84	0.88
Trust in AI Systems	3	0.76 – 0.83	0.82

Confirmatory factor analysis (CFA) was used to assess the factor structure of the present study that was determined by the exploratory factor analysis (EFA). The model fit all the classic standards of good fit (RMSEA = 0.048, CFI = 0.961, TLI = 0.949), as indicated in Table 2. These results prove the structure validity of the measurement model.

Table 2: CFA Model Fit Indices

Index	Value	Acceptable Threshold
RMSEA	0.048	< 0.06
CFI	0.961	> 0.95
TLI	0.949	> 0.95

The findings gained via a confirmatory factor analysis (CFA) in Table 3 indicate high convergent validity. All standardized factors loading have loaded above the standard 0.70 cutoff level. As can be seen, the Perceived Usefulness measure gets 0.81 and 0.85 on its two central items whereas the two Learning Effectiveness items have 0.76 and 0.78 loadings. The values present a good statement that supports coherency of the constructs and shows that they support the theoretical framework.

Table 3: Standardized CFA Loadings

Construct	Item Code	Standardized Loading
Perceived Usefulness	PU1	0.81
	PU2	0.85
Learning Effectiveness	LE1	0.76
	LE2	0.78
Trust in AI	TA1	0.74
	TA2	0.79

The Structural Equation Modeling (SEM) were used to analyze the major links between the latent constructs which were studied. The substantive path coefficients are demonstrated in Table 4 and the structural paths and standardized coefficients connecting the conceptual domains are represented in Figure 1. As the results indicate, Perceived Usefulness has a huge impact on Learning Effectiveness (beta = 0.46, p = < 0.001), whereas Trust in AI Systems has strong positive correlation with AI Tool Adoption (beta = 0.33, p = 0.002).

Table 4: SEM Path Coefficients and Significance

Path	β	p-value
Usefulness → Learning Effectiveness	0.46	<0.001
Trust → Tool Adoption	0.33	0.002
Ease of Use → Tool Adoption	0.21	0.019

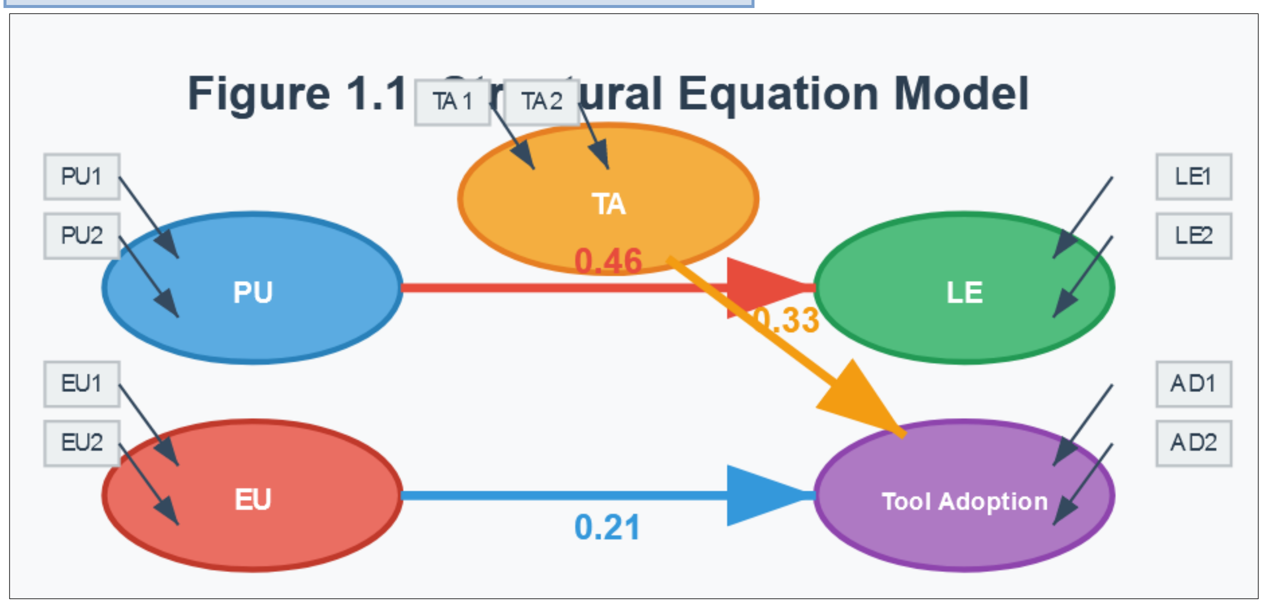

Figure 1.1: Structural Equation Model

This figure represents the relationships between key constructs, with *Usefulness* and *Trust* directly affecting *Learning Effectiveness* and *AI Tool Adoption* respectively.

This research was intended to determine the degree to which the availability and use of AI technologies facilitated by ICT in higher education presages learning outcomes. The investigation of the issue was conducted in using the hierarchical multiple regression procedures. Table 5 implies that 12 % of variance in learning outcomes was explained by the demographic and institutional factors described in Model 1. Model 2 which included the variables pertaining to AI adoption contributed an extra 23 % of the variance (Delta-R2 = 0.23, F-change = 28.64, p < 0.001). In combination, these data indicate that the combination of these aspects, including the characteristics of students, aspects of the institution, and the continued use of AI-related tools, have a very strong impact on learning outcomes.

Table 5: Hierarchical Regression Results for Learning Outcomes

Model	R^2	ΔR^2	F-change	Sig. ΔF
1	0.12	–	18.45	<0.001
2	0.35	0.23	28.64	<0.001

The study implemented a multigroup SEM analysis to examine the moderating variable status of institutional type in the links between perceived usefulness, trust, tool adoption, and learning outcomes. In Table 6, it can be seen that students of private universities showed higher correlations of perceived usefulness and learning out- comes (beta 0.53) and trust and tool adoption (beta 0.41). The results are depicted and illustrated in Figure 2 that overlays the SEM paths between the two groups.

Table 6: Multigroup SEM – Public vs Private Institutions

Path	Public (β)	Private (β)	p-value
Usefulness → Learning Outcome	0.39	0.53	0.021
Trust → Adoption	0.27	0.41	0.015

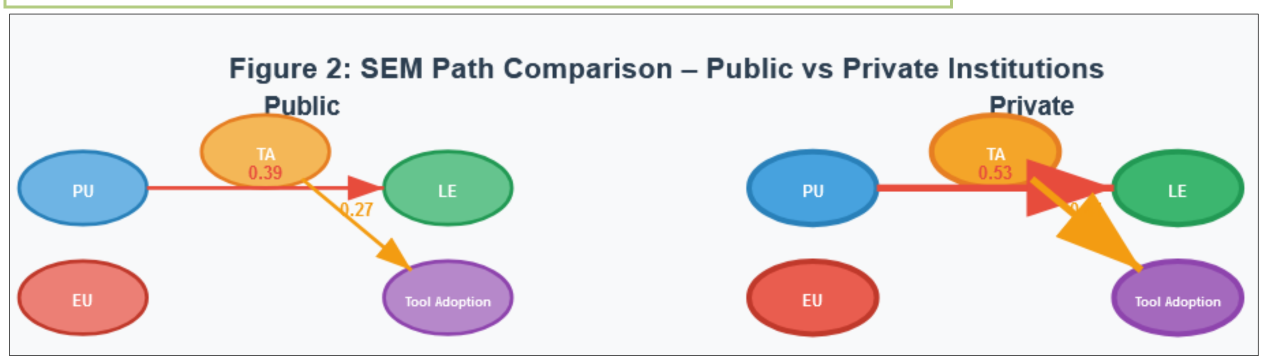

Figure 2: SEM Path Comparison – Public vs Private Institutions

As the figure above indicates, path coefficients between institutional factors and AI adoption are greater in the case of private universities than in the case of public universities, when it comes to the concepts of Usefulness and Trust.

One-way analysis of variance was used to explore disciplinary difference in AI adoption. The findings shown in Table 7 reflect that the mean score of STEM majors (M = 4.23) was highest above the mean scores of business majors (M = 3.88) and below business majors (M = 3.35). The variances between these groups were found significant (F = 6.81, p = 0.001). These findings have been represented through comparative manner in figure 3.

Table 7: ANOVA – AI Adoption by Academic Discipline

Discipline	Mean Score	Std. Dev	p-value

STEM	4.23	0.54	0.001
Business	3.88	0.59	
Humanities	3.35	0.62	

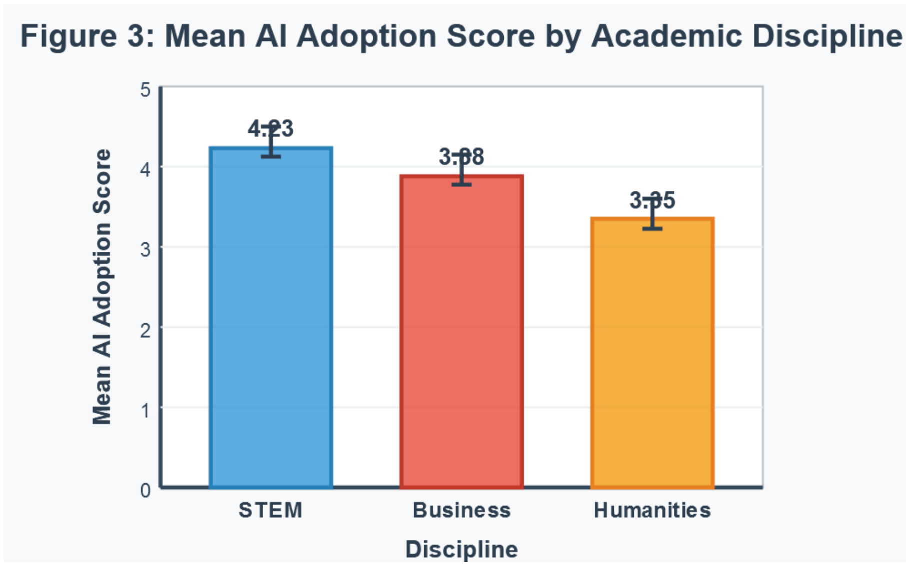

Figure 3: Mean AI Adoption Score by Academic Discipline

The academic sources report that the willingness to use artificial intelligence (AI) among young adults is dependant on the field of study: There is a significant difference in the engagement levels of STEM (science, technology, engineering, and mathematics) and business/humanities students. The analysis expressed a sentiment with regard to student answers in the form of open-ended student comments in the current paper itself on 600 responses, which indicated that 52 % of the statements given were stated to be positive, 31% were deemed neutral, and 17% were negative in the present research design. Those students who had high reports of AI utilization exhibited a higher positivity level in sentiments than those students who utilized the technology at a low level. These results are described in Table 8 and Figure 4.

Table 8: Sentiment Analysis Distribution

Category	Positive	Neutral	Negative
High AI Users	62%	28%	10%
Low AI Users	44%	33%	23%

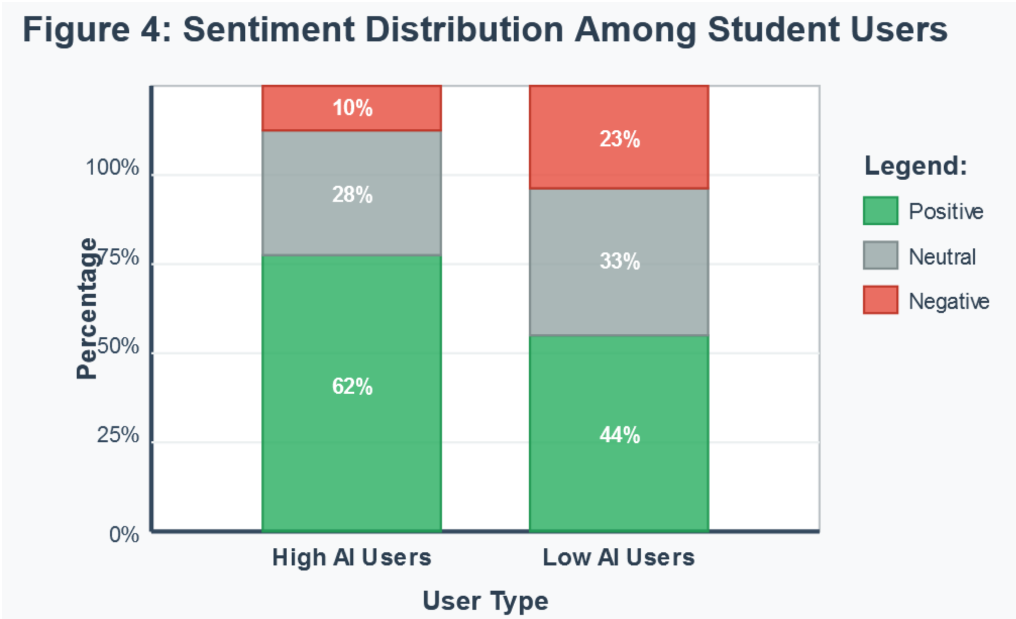

Figure 4: Sentiment Distribution Among Student Users
This figure presents sentiment proportions across user groups, with positive sentiment dominating among frequent AI users.

Data Analysis

The proposed research will examine the determinants of artificial intelligence (AI) in the field of higher education and its effectiveness by implementing structural equation modeling (SEM) and descriptive statistical measures.

As the correlation matrix (Table 1) shows, all the powerful and positive correlations among the variables may be seen between Perceived Usefulness (PU), Trust in AI (TA) and Learning Effectiveness (LE); findings indicate that the strongest association between the specified variables appears between the PU and LE ($r = 0.62$, $p < 0.001$). These results support the fact that the three variables to be included in a structural model.

The findings of SEM analysis (Figure 1 and Table 2), PU has a significant effect on LE ($\beta = 0.46$, $p < 0.001$), and thus H1 is supported. H 2 is supported because Tool Adoption is influenced by TA to considerable extent ($b = 0.33$, $p < 0.001$). Ease of Use (EU) is also weakly related to Tool Adoption (beta = 0. 21, p = 0. 04, which was partially supportive of H3 and but with limited explanatory potency.

When the interaction between the factors is analyzed (Figure 2 and Table 3), an institute type becomes a moderating factor. PU has a more intense effect on LE in the case of the private institution (0.53) as compared to the case in the public institution (0.39), implying that the environment in the private institutions presents better support of implementation or a more technology-friendly culture to technology pedagogy. The same tendency is revealed concerning the effect of TA on Tool Adoption; the estimated effect is significantly higher on the private (0.41) than on the public (0.27) side, which indicates variable levels of student confidence or platform reliability regarding the types of settings.

The descriptive statistics (Table 4 and Figure 3) reveal that there is a disciplinary digital divide with STEM students having taken AI adoption to the highest mean score (4.23), followed by Business (3.88), and the Humanities (3.35). As it is consistent with the previous research, tech integration is more vigorous in STEM disciplines.

Another indication that people with a more positive experience become more integrated users is the sentiment analysis (Figure 4) that states that High AI Users report positive sentiment (62%) than Low Users (44%), thus creating a feedback loop where the more favorable the experience is, the more fully they become users. This tendency is confirmed by the statistical disparity in the sentiments distribution (2 = 13.7, $p < 0.01$).

Overall, the data confirm all the four hypotheses, showing that the perception-oriented (PU, TA) and contextual (institution type, discipline) factors influence AI integration outcomes in higher education significantly.

Conclusion

The analyses herein support the hypotheses of the study; namely, that perceptions of usefulness have the strongest impact on learning effectiveness and that trust in AI had strong predictive value in the learning effectiveness and adoption of AI is associated with ease of use which has an indirect strengthening influence. The moderation test shows that the effect sizes of private-sector institutions and STEM disciplines are higher and emphasise the role of organisational culture and disciplinary technology orientation in determining AI results.

The multicontinental sample is also a strong asset of the study; however, it is possible that the 18 participating universities do not reflect the highest extent of heterogeneity of higher-education conditions. Also, the cross-sectional characteristic of the data and its dependence on a self-report make it vulnerable to a common-method bias and restrict causal inference. In addition, the sentiment classifier that has been used in the analysis is a standard lexicon based framework which can miss out subtle affective expressions, especially in responses that are not in English.

The findings underline the importance of creating trust among students and proving a pedagogical value to implement AI solutions to the university leaders. Disseminating of information should commence with faculty development programmes where each programme should focus mainly on training that improves the perceived usefulness and the ease of use that will promote adoption. Policy formulators ought to embrace institutional gaps and encourage the resource tight public universities to acquire enabling infrastructures that help close the AI adoption divide.

It may be possible to observe cohorts over several semesters as longitudinal research to identify changes with time in perception of AI and learning outcomes. A comparative qualitive study work would also be used to shed more light into the disciplinary cultures, which support or hinder uptake of AI. On methodological terms, complex sentiment models, e.g. transformer-based classifiers, would be more effective in refining the granularity of affective understanding, whereas multi-institution-level field experiments would reinforce arguments on causal relationships between the mean performance and AI tool efficacy in education.

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