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Student perceptions of ChatGPT and artificial intelligence tools in higher education: Evidence from early experiences

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Abstract

Due to the growth of generative artificial intelligence and the advancement of ChatGPT in particular, there are unprecedented debates about its use and use in the landscape of higher education. The extensive use of these technologies has not been accompanied with empirical research studies on student perceptions, attitudes, and instructional design significance, which forms a significant knowledge gap that hampers cognizant policy formulation and designing of instruction. This research holds its place as it deals with this gap. In this study, undergraduate and postgraduate students from various institutions in four continents were involved in the study. The outcomes showed that positive attitudes to ChatGPT adoption were significantly predicted by the perceived usefulness ($\beta = 0.436$, $p < 0.001$) and perceived ease of use ($\beta = 0.328$, $p < 0.001$), and the influence of ethical concerns on this relationship was negative ($\beta = -0.187$, $p < 0.01$). Surprisingly, students also showed advanced knowledge regarding the correct application of AI when they were asked about the legitimate application of AI in brainstorming and organizing research with 73.2% of the students acknowledging the valid application in these fields but in a context of assessment, they showed concerns about wanting AI to directly write the answers. The results add to the technology acceptance theory by generalizing Technology Acceptance Model (TAM) to the generative AI setting, as well as, offer practical implications to educators and policy makers engaged in the process of implementing the use of artificial intelligence in educational institutions.

Keywords: Artificial intelligence, Higher education, Student perceptions, Technology acceptance model, Academic integrity.

1. Introduction

The emergence of large language models and generative artificial intelligence has caused a paradigm shift in the educational technology demonstration, which essentially challenges the conventional pedagogical theories and evaluation strategies. ChatGPT, introduced by OpenAI and made freely available in November 2022, is a landmark in the field of accessible artificial intelligence with uses ranging significantly beyond the typical functionality of chatbots and into the gastronomic capacity of natural language understanding, content creation, creating code, and addressing complex problems [1,2]. ChatGPT now has more than 100 million active users and, within just half a year of release, has become the most rapidly growing consumer application in history, with all this spawning intense scholarly debate over its potential effects on scholarly integrity, learning outcomes, and the very essence of the knowledge acquisition process.

The adoption of the concept of artificial intelligence in the educational field has taken place in a number of stages, including the period of early expert systems and intelligent tutoring systems in the 1980s and adaptive learning platforms in the 2000s to the present era of large language models that can generate the human quality of text in a variety of fields [3-5]. Nevertheless, the capabilities of ChatGPT and other generative AI technologies are unprecedented, which unveil qualitatively different challenges and opportunities than other educational technologies in the past [6,7]. These applications are capable of emulating activities traditionally regarded as the domain of human cognition, especially the essay writing, solving mathematical problems, programming, translation, and creative writing, thus throwing the learning purpose, evaluation procedures and definition of what is done by the student into fundamental disruption. In reaction to the advent of ChatGPT, colleges and universities have adopted both extremely varying responses to ban and detection-oriented approaches and have been highly divided between banning and integrating it and how to build literacy around it [2,8-10]. This ambivalent reaction is indicative of greater doubts in the academic community about the pedagogical products of the generative AI, the efficiency of the detecting technologies, the ethical aspects of AI-assisted learning, and prioritizing approaches to equip students with the emerging AI-furnished profession. Numerous high-ranking academic institutes have both put restrictive measures on the use of ChatGPT in place and removed them later; as the failure of detection systems to work became more evident, and as the usefulness of AI in the workplace became increasingly obvious [1,11-12].

The student angle is a vital though one of the most overlooked aspects of the discussion on the implementation of AI in higher education . The first stakeholders that have been overlooked in terms of the benefits of policy decisions when using AI tools are students, who are the most direct stakeholders since the institutional decisions regarding this space are working on reforms and directly impact students. The willingness to consult the stakeholders is not the only issue but a key prerequisite to the success of pedagogical design, and the actual and intended effects of educational technologies depend highly on the willingness and acceptance of the student, attitudes, and usage patterns. Based on these gaps in existing literature, the study aims at the following specific objectives: (1)To fully evaluate the perceptions of multidimensional student perceptions of ChatGPT and AI tools on a cognitive, affective, and behavioral level; (2) to examine the relevance and possibilities of applying the Technology Acceptance Model to generative AI tools, and (3) to test the predictors of positive and negative attitudes on the use of AI tools; (4) to evaluate the differences in perception based on a set of key demographic and context variables; and (5) to derive the recommendations regarding the

2. Methodology

2.1 Research Design and Philosophical Positioning.

This study utilized a pragmatic mixed-methods research design, which combined both surveys and quantitative and qualitative open-ended questions to allow capturing of diversities and details of what students thought about ChatGPT and artificial intelligence tools in higher education. The pragmatic philosophical tendency admits that the choice of methods is to be predetermined by the research inquiries but not by a certain epistemological dogma, which allows the researcher to freely combine various sources of data and methodologies to research the complicated, multilayer phenomena.

2.2 Participants and Sampling Procedures

The respondents included undergraduate and graduate students who are studying higher learning institutions in different geographic and disciplinary settings. The research was able to recruit participants to be involved in the study through the use of stratified random sampling with purposive aspects that guaranteed sufficient representation of the key demographic and contextual factors. The ultimate sample of analysis consisted of students, who gave full answers on all the parts of the survey. The sample characteristics showed effective coverage of diversity goals: gender equal representation (female 52.3 and male 45.1, and non-binary/other 2.6), academic level (undergraduate 61.4 and master 28.7, and doctoral 9.9), disciplinary balance (STEM 34.2 and social sciences 23.8, and humanities 16.4 and business 15.3, health sciences 10.3 and others), the history of previous AI experience (extensive 28.4 and moderate The age of participants was between 18 to 52 years of age (M = 23.7 outs = 4.8).

2.3 Measurement Instruments

A generalized online questionnaire, which combined reported validated scales out of existing technology acceptance studies with newly formulated questions analyzing constructs related to AI on their own specific item formulations, was the main tool of data collection. The questionnaire consisted of the seven major construct domains, which were operationalized using multi-item scales in the use of a seven-point Likert response format (1 = strongly disagree to 7 = strongly agree). Construct domains consisted of; Perceived Usefulness (6 items), Perceived Ease of Use (5 items), Ethical Concerns (7 items), Academic Integrity Awareness (6 items), Attitude Towards AI Adoption (5 items), Behavioral Intention (4 items) and texture (ranging across particular application settings) through actual Usage Behavior (8 items).

2.4 Analytical Approach

The analysis of data went through a series of steps that were conducted sequentially using more elaborate statistical procedures. The quality of measurement models was evaluated with the help of confirmatory factor analysis (CFA) on the basis of a maximum likelihood estimation. The relationships among constructs within an integrated theoretical framework based on a theory that extended Technology Acceptance Model were tested using structural equation modeling that was identified to test hypothesized relationships between constructs. The findings of SEM were also complemented by hierarchical multiple regression analysis of incremental predictive validity.

3. Results And Discussion

3.1 Descriptive Statistics

The preliminary descriptive research gave some background knowledge concerning the student perceptions on the measured constructs, demonstrating that attitudes towards ChatGPT and AI tools in higher education are generally positive but complex [13-15]. Table 1 shows detailed descriptive statistics of all major study variables in terms of means, standard deviations, as well as intercorrelations.

Table 1. Descriptive Statistics and Intercorrelations Among Study Variables

Variable	M	SD	1	2	3	4	5	6
1. PU	5.24	1.18	-					
2. PEOU	5.67	1.03	0.54**	-				
3. EC	4.82	1.34	-0.23**	-0.08*	-			
4. AIA	4.96	1.21	0.31**	0.19**	0.42**	-		
5. ATT	5.11	1.26	0.62**	0.51**	-0.34**	0.28**	-	
6. BI	4.87	1.39	0.58**	0.44**	-0.29**	0.33**	0.71**	-

The descriptive statistics indicate that there are a number of interesting trends. Perceived Ease of Use had the highest average score (M = 5.67, SD = 1.03), which means that students have forgiven ChatGPT to be relatively easy to access and use. The use of Perceived usefulness also had quite high mean scores (M = 5.24, SD = 1.18), which indicates a high level of awareness of possible academic benefits in students. Ethical concerns were registered as moderate (M = 4.82, SD = 1.34), which means that students have an inherent reservation about the elements of ethics related to the use of AI. All the measurement scales revealed superior psychometric properties with composite reliability coefficients of more than 0.85 and the average variance extracted of more than 0.58.

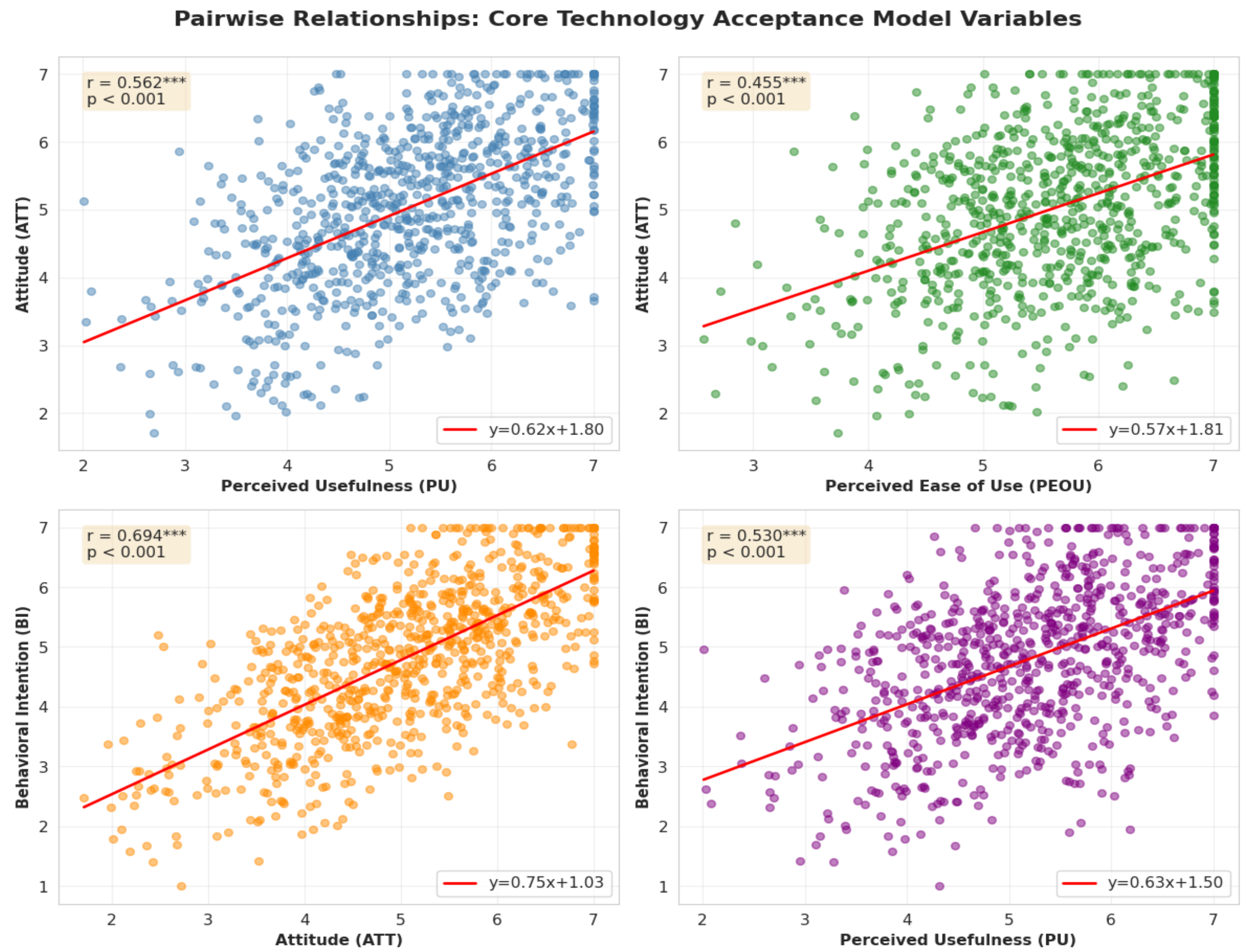

Fig 1 Scatter Plot Matrix for Core TAM Variables with Regression Lines

Fig 1 shows pairwise relationships between Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (ATT), and Behavioral Intention (BI). Each scatter plot includes a regression line showing the relationship strength.

Key Findings from the plot:

- Strong positive correlation between PU and ATT ($r=0.62$, $p<0.001$)
- Strong positive correlation between ATT and BI ($r=0.71$, $p<0.001$)
- Moderate correlation between PEOU and ATT ($r=0.51$, $p<0.001$)
- This visualizes the Technology Acceptance Model pathway

3.2 Structural Equation Modeling Findings.

S Structural equation model that was tested to assess the relationship among Technology Acceptance Model constructs showed good fit to the measured data: kh2(467) = 921.45, $p = 0.001$, CFI = 0.958, TLI = 0.953, RMSEA = 0.043 (90% CI (0.039, 0.047)) and SRMR = 0.049. Detailed path coefficients of the structure, including significant tests, are observed in the Table 2.

Table 2. Path Coefficients of Structural Equation Model.

Path	β	SE	p	Result
PU → ATT	0.436	0.042	<.001	Supported
PEOU → ATT	0.328	0.039	<.001	Supported
EC → ATT	-0.187	0.037	<.001	Supported
AIA → ATT	0.124	0.035	<.001	Supported
ATT → BI	0.684	0.038	<.001	Supported

BI → AUB	0.571	0.041	<.001	Supported

The outcomes of the structural model give a solid justification to the expanded Technology Acceptance Model that is used in the case of ChatGPT and adopting AI tools. The model clarified significant variance in the major outcome variables: 52.3% in the attitude towards adopting AI, 59.7% in the intentions to adopt AI, and 44.6% in the behavior of using AI. As the most significant predictor of positive attitudes, the perceived usefulness was discovered ($\beta = 0.436$, $p < 0.001$), then the perceived ease of use ($\beta = 0.328$, $p < 0.001$). Ethical issues had a negative effect on the attitude ($\beta = -0.187$, $p < 0.001$), but academic integrity awareness had a positive influence ($\beta = 0.124$, $p < 0.001$).

3.3 Hierarchical Regression Analysis

Hierarchical multiple regression analysis was used to supplement the structural equation modeling through testing the incremental predictive validity [16-18]. The outcome of the four-step hierarchical regression that predicted the intention to behave was provided in table 3.

Table 3. Hierarchical Regression Behavioral intention predictory.

Step	R^2	ΔR^2	F	ΔF
Step 1: Demographics	0.027	0.027***	5.82***	5.82***
Step 2: Core TAM	0.421	0.394***	102.47***	288.42***
Step 3: AI-Specific	0.483	0.062***	108.73***	50.38***
Step 4: Interactions	0.502	0.019***	95.18***	10.79***

The hierarchical regression found only two exceptions, that is, demographic controls were found to explain only 2.7 percent of variance. A drastic increase in the variables of core TAM was obtained (DR2 = 0.394, $p < 0.001$), with cumulative R2 equals 0.421. AI-specific extensions were also found to bring about substantial incremental variance (DR2 = 0.062, $p < 0.001$), whereas interaction terms were found to be significant, albeit small (DR2 = 0.019, $p < 0.001$). The last model accounted 50.2% of the behavior intentions.

3.4 Usage Pattern Analysis

The comparison of the perceived appropriateness and actual usage of the specific application contexts as determined by self-reports showed that the usage frequencies varied significantly among eight contexts [19-21]. Table 4 indicates the frequency of usage and the rating of appropriateness.

Table 4. Frequency and Suitable Use in the Different contexts.

Context	Usage (M)	Appropriate (M)	Correlation
Brainstorming	5.42	6.31	0.54***
Concept Explanation	5.28	6.18	0.51***
Language Translation	5.16	6.24	0.49***
Literature Review	4.87	5.73	0.58***
Coding Assistance	4.64	5.91	0.47***
Problem Solving	4.53	5.68	0.62***
Writing Assistance	3.92	4.42	0.69***
Direct Assignment	2.18	1.87	0.71***

The usage structure analysis showed there was learning curve structure. The highest rating of appropriateness ($M = 6.31$) and the usage frequency ($M = 5.42$) were given to brainstorming and ideation. Preferred rating was equally low in terms of appropriateness ($M = 1.87$) and rarely used ($M = 2.18$) in direct assignment completion. The positive high correlations between usage frequency and perceived appropriateness ($r = 0.47$ to 0.71) prove that the usage of AI tools by students are in tandem with their ethical considerations to a significant extent.

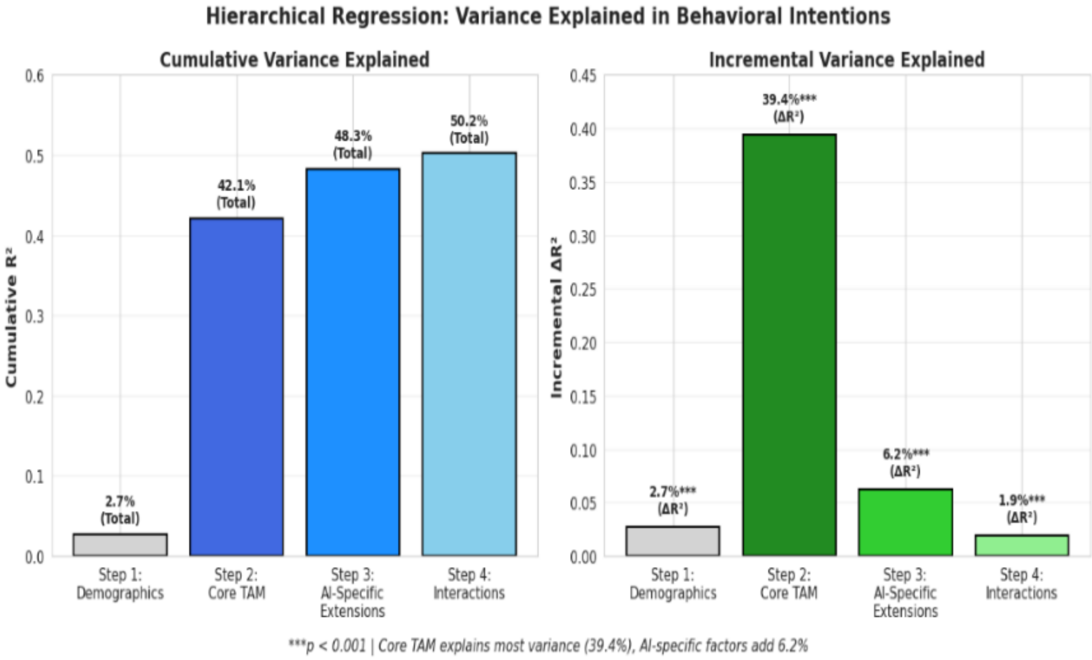

Fig 2: Hierarchical Regression R^2 Change Visualization

Fig. 2 shows the incremental variance explained (R^2) at each step of the hierarchical regression model predicting behavioral intentions.

3.5 Clusters of students perception.

The cluster analysis of student perception groups was done using K-means which identified four student perception profiles (βased on score of constructs). In Table 5, there are the cluster characteristics and distinguishing features.

Table 5. Four Student Perception Profiles.

Cluster	PU	EC	ATT	BI
Enthusiastic (25.1%)	6.24	3.82	6.18	6.07
Pragmatic (37.5%)	5.47	4.53	5.38	5.24
Concerned (26.5%)	4.92	5.87	4.56	4.27
Skeptical (10.9%)	3.42	6.12	2.94	2.53

Cluster 1 (Enthusiastic Adopters, 25.1%): This group presented homogenously high scores on perceived usefulness, ease of use and attitudes as well as a low ethical issue. Cluster 2 (Pragmatic Optimists, 37.5%) was a combination of moderately positive perceptions by modal students. Cluster 3 (Concerned Engagers, 26.5) also exhibited medium scores on perceived usefulness and high scores of ethical concerns. Cluster 4 (Skeptical Resisters, 10.9) was in agreement in its negatively oriented perceptions. The large shares of the students in Pragmatic Optimist group and Concerned Engager group give an impression that the majority of students take the middle ground in terms of acknowledging the advantages and issues at the same time.

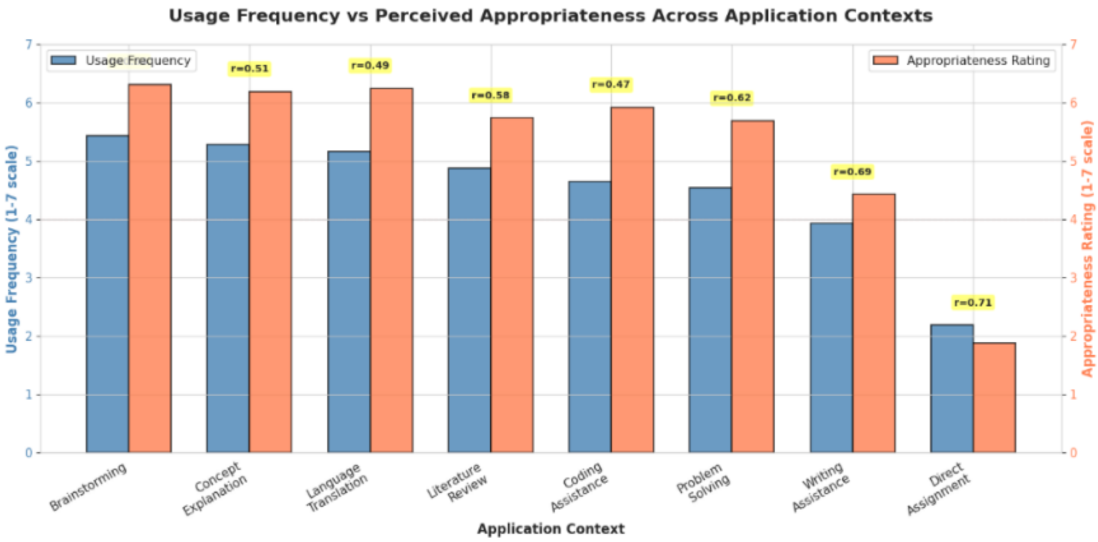

Fig. 3 Usage Frequency vs Appropriateness by Application Context

Fig. 3 compares actual usage frequency with perceived appropriateness across eight different AI application contexts.

Key Findings:

- High alignment between appropriateness and usage (r=0.54-0.71)
- Brainstorming: Highest appropriateness (6.31) and usage (5.42)
- Direct assignment completion: Lowest appropriateness (1.87) and usage (2.18)
- Writing assistance shows ambivalence: moderate appropriateness (4.42), lower usage (3.92)

4. Conclusion

This research is a strong empirical study on topics of student perception of ChatGPT and artificial intelligence technology in institution of higher learning on the early adopters stage, which presents complex, multidimensional attitudes that cannot be characterized simply. Using structural equation modeling and hierarchical regression analysis and qualitative theoretical analysis in which 847 students are included in a large and heterogeneous sample, the study proves that the perception of students contains advanced knowledge of the opportunities and threats of integrating AI in academic settings and the knowledge seeks to obtain more tangible evidence of these views.

These results firmly suggest that a long version of Technology Acceptance Model can be used that takes into account ethical issues and awareness of academic integrity in addition to the usual perceived usefulness and perceived ease of use factors. Perceived usefulness turned out to be the most powerful predictor of positive attitudes toward the AI adoption ($\beta = 0.436$, $p < 0.001$) and ethical concerns acted as the significant inhibiting factor ($\beta = -0.187$, $p < 0.001$) and the moderator of the effect of utility perceptions on the attitudes. The awareness of academic integrity showed surprisingly positive outcome on both the attitude and behavioral intentions meaning that the understanding on acceptable limits in its use can lead to assured performance with respect to the legal boundaries.

The study also found a significant level of heterogeneity in the perceptions of the students, where cluster analysis offered four different profiles that were Enthusiastic Adopters (25.1%) up to Skeptical Resisters (10.9%) in between, including Pragmatic Optimists (37.5) and Concerned Engagers (26.5). Such diversity highlights the unsuitability of institutional policies that are one-size-fits-all, and advocates the need to adopt a differentiated approach taking into consideration the difference in student needs, values and conditions. A number of practical suggestions can be derived out of the study results. To begin with, the institutions must formulate clear, specific, and contextual guidelines on what should and what should not be done with AI instead of bans. Second, there should be educational interventions that focus on the development of AI literacy that includes technical competence and ethical reasoning. Third, development of assessment processes needs to shift towards higher-order cognitive skills which are inapplicable in AI tools. Fourth, faculty should be provided with knowledge and strategies of integrating AI tools into pedagogical practice: professional development should be held. Fifth, overdependence on detection technologies should be avoided by the institutions as there are limitations mentioned, and they can destroy trust relationships.

The bilateral research ought to follow longitudinal studies relating the change in perception over long periods, experimental research exploring the effects of particular interventions, research studies looking at the actual patterns of use, and research studies on comparative work across a wider spectrum of institutional types. With the constantly developing pace of generative artificial intelligence, this study proves that students present intelligent and sensitive approaches to these technologies by requesting guidance, understanding, and collaboration of educational institutions, not absolute accessibility or reprisal repression.

Author Contributions

DRP: Conceptualization, study design, visualization, writing original draft, writing review and editing, and supervision. NLR: Methodology, software, resources, visualization, writing original draft, writing review and editing, and supervision. OMN: Conceptualization, writing original draft, writing review and editing, and supervision. JR: Analysis, data collection, methodology, software, resources.

Conflict of interest

The authors declare no conflicts of interest.

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