



Effects of ChatGPT Use on Academic Achievement

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Abstract— The rapid spread of AI tools such as ChatGPT in higher education has elicited interest in their effects on students' learning outcomes. This study investigates students' uses of ChatGPT in relation to university students' academic achievement, and focuses on student engagement, personalized learning experience, and student retention/dropout as potential intervening roles. The study employed a quantitative questionnaire survey of 151 business and management undergraduates in March and April 2025. Respondents responded to a 5-point Likert-scale ordered structure questionnaire tapping 5 constructs: (1) AI use; (2) student engagement; (3) personalized learning experience; (4) student retention/dropout; and (5) academic achievement. Respondents' reported use of ChatGPT clustered in two domains: (a) aiding in STEM-related coursework, research, and analysis, and exam prep; and (b) language learning and translation. In our structural model, ChatGPT use explained 69.3% of the variance in student retention/dropout ($R^2 = .693$). The latter, in turn, due to improved focus, persistence, and active engagement, explained 38.5% of the variance in learning motivation ($R^2 = .385$). Increased motivation, in turn, related positively to a number of dimensions of academic achievement—creativity and critical thinking, ethical awareness, and knowledge/analysis transfer. Respondents also reported the practical utility of AI tools, time savings, and ease of synthesizing information expeditiously across topics. Exploration analyses reflected low positive correlations between outcome and some national cultural value orientations (e.g., social responsibility awareness, respect for tradition, low uncertainty avoidance, in-group fidelity, long-term persistence, and caring for others). The results, in aggregate, show that students' ChatGPT utilization can serve as a great supplementary resource to raise engagement and retention and have small but positive effects on academic achievement. The findings must be interpreted in terms of the study's cross-sectional research design and limitations in terms of self-reports.

Keywords — *Engagement, Personalized Learning Experiences, and Student Retention, Cultural values*

I. INTRODUCTION

Since 2022, large language models (LLMs) such as ChatGPT have sparked new hope—and controversy—over higher education. Their supporters think that conversational

AI can offer immediate, personalized explanations to keep learners engaged and encouraged [1], and adaptive systems in general can tailor content and pace to individual students, increasing participation and outcomes [2]. Educators, on the other hand, point to potential risks: over-reliance on AI, loss of critical thinking, violations of academic integrity, and spotty accuracy of model responses [3], [4].

The empirical evidence becomes more extensive but subtle. Meta-analyses portray aggregate positive effects of generative-AI or ChatGPT deployment on learning outcomes, higher-order processing, and affective-motivational states [5]–[7]. One large randomized controlled study also demonstrated an AI-tutoring strategy to outperform in-class active learning in an operational university setting [3]. Effectiveness, however, hinges on implementation: adoption and effect reduce to pedagogy, integration in coursework, and student dispositions; difficulties in maintaining engagement and in aligning AI deployment and setting objectives are reported across research studies [8], [9].

Contextual contribution. Mongolia offers a unique environment for investigating AI in higher education, characterized by heterogeneous upper-secondary preparation, salient bilingual requirements in university studies, and non-negligible outbound student mobility. In the paradigm of Hofstede, such characteristics plausibly shape the way students pursue structuring, power, and feedback in learning [10]. Since the Hofstede platform discriminates tested national scores against una tested guesstimates—and warns against applying the latter to scientific analysis—we do not submit numeric scores for Mongolia; instead, we consider culture-relevant associations identified in the data as hypothesis-generating to be substantiated with tested measures in future multi-site and longitudinal studies [11].

Against this context, this research studies ChatGPT use in relation to university students' academic results, in terms of predicting five dimensions: use of AI, student engagement, personalized learning experience, students' retention/dropout, and collective academic attainment. We speculate that AI tools function primarily as learning accommodations whose impacts flow through engagement and personalization to affect performance and long-term attainment. This research,

set in a Mongolian university context, contributes evidence from beyond Western, industrialized settings to put reported AI advantages to the test and identify under which conditions they materialize.

II. LITERATURE REVIEW

A. Artificial Intelligence in Education

Artificial intelligence (AI) increasingly shapes learning spaces through intelligent tutoring, automatic feedback, adaptable systems, and large language models (LLMs) such as ChatGPT. Effectively implemented, these provide personalization of study, release teachers from repetition, and can support better outcomes [12], [13]. Real-time analytics also enable data-informed instruction and more responsive practice [14]. However, responsible adoption requires cross-portfolio regard for privacy, equality of access, and over-reliance risk to displace criticality [15], [16]. Effective integration thus places innovation and ethical and pedagogic protection in equilibrium.

B. AI and Academic Achievement

The research often indicates positive correlations between artificial intelligence (AI) utilization and learning performance, often by means of increased engagement and personalization [17], [13]. As one example, it's possible for AI systems to deliver personalized feedback and scaffolding in ways that benefit diverse needs students [17]. The findings, however, depend on how one applies AI—digital literacy and test design (as well as faculty guidance) moderate effects; misuse of generative AI can distort academic integrity or bypass higher-order comprehension [16], [14]. In summary, there's justification in the research base for guarded optimism: AI can increase performance when it's implemented within good pedagogy.

C. Research Model

To study the ChatGPT and student success relationship, we developed six constructs:

1. AI Use—How often and for research-related reasons, students use ChatGPT or similar tools [12].
2. Student Engagement — Behavioral, cognitive, and affective investment in learning activities [18].
3. Individualized Learning Experience — Adapted content, pace, and feedback at personal level [17].
4. Student Academic Performance — Test scores and assignment quality as proximal outcomes [13]. Academic Achievement — Cumulative GPA or on-time progress as distal outcomes [14].
5. Student Retention/Dropping Out — Secular and contemporary estimates, founded upon past theory and validated measures [19]–[21].

The research tool was constructed based on these constructs, and the collected data allowed a multidimensional exploration of the educative effect of AI.

D. Use and Adoption of Artificial Intelligence in the Education Sector of Mongolia

In Mongolia, AI education is still in its infancy, and there is increased interest, both from students and teachers. Formal training in class in AI tools is still in its infancy, while informal

access, especially to generative AI, like ChatGPT, is on the increase. Students in tertiary institutions, particularly those in Ulaanbaatar, are increasingly utilizing ChatGPT for translation, content generation, and writing, despite a low awareness of ethical uses, digital literacy, and plagiarism avoidance [22].

Adoption challenges include inadequate infrastructure, limited AI interfaces in Mongolian, and policy support gaps. Faculty also express fears of unfairness, overdependence, and loss of critical thinking capacity. While these challenges exist, AI's potential to fill gaps in personalized learning, provide live academic support, and reduce teacher shortages provides it with immense promise as an innovation. In order to be effectively adopted in Mongolia's learning culture, there must be coordinated responses in training, localization, and policy formulation.

E. Mongolian Secondary-to-Tertiary Transitions: Readiness, Examinations, and Mobility

In recent years, an ever-greater share of high-achieving secondary-school graduates in Mongolia have gone directly into foreign bachelor's programs, consistent with reported increases in UNESCO statistics and host-country indicators [23], [24]. At the same time, Mongolia's PISA 2022 results indicate below-OECD-average mean performances in reading, science, and mathematics, as indicators of systemic gaps in upper-secondary preparedness [25]. National entrance-exam indicators show this same trend: recent cohorts have scored lower means, including in mathematics (for example, the average math score fell to 19 in 2025), and declines in several subjects compared to 2024. Such gaps in preparedness likely lead to difficulties in understanding coursework and, in certain students, delayed graduation or drop out—mechanisms widely described in retention scholarship [19]. Against this context, our study examines whether—and how—AI tools, and particularly ChatGPT, can support engagement and persistence and provide better academic outcomes.

F. Mongolian cultural dimensions (Hofstede framework)

We understand contextual variation with Hofstede's six-dimensional framework—power distance, individualism—collectivism, masculinity—femininity, uncertainty avoidance, long-term orientation, and indulgence—and the theory that national value configurations influence preferences for control, autonomy, formality, and constructive feedback in learning [10]. On Hofstede's official website, the comparison tools clearly label validated country scores versus non-validated guesstimates and clearly warn that non-validated values must not be applied in scientific studies [11]. At the time of writing, Mongolia lacks commonly available, validated scores in the Hofstede table accessible on the official site; therefore, we do not report numeric values and treat culture-associated patterns in the data as exploratory. Theoretically, the Hofstede framework is still beneficial to framing potential processes—for instance, increased uncertainty avoidance might make students more dependent on AI for form and explanation, while power-distance values might influence the acceptability of AI as a tutorial expert—all this providing a basis for future, multi-site and longitudinal studies in Mongolia to testable hypotheses [10], [11].

TABLE I. ENTRANCE-EXAM SCORE^a, 2021-2025

Year	Math.	English	Social studies
2021	26	41	59
2022	26	34	50
2023	27	35	42
2024	24	35.7	43
2025	19	35.3	35.1

^a Source: on the official site of the National Statistics Office of Mongolia

Past five-year entrance-exam trends support this question further. National means in areas most related to our programs—Mathematics, English, and Social Studies—have trended down (e.g., 2021-2025 trends reported by EEC in the official National Statistics Office of Mongolia website). Published means by EEC, notably, do not include those candidates who convert international test scores (e.g., SAT, IELTS) to entrance-exam equivalent scores. In 2025, 3,661 equivalency applications were made online, and 2,598 were approved; 48.3% and 41.3%, respectively, of those who applied sought equivalency in SAT and IELTS. In 2025, 43,318 students entered the national exam in 28,637 and 27,122 in mathematics and English, respectively. These public counts, in aggregate, indicate equivalency approvals comprise roughly 3.6% of those who tested in math and ~4.0% of those who tested in English. These equivalency candidates, in aggregate, have strong language or math proficiency, as would correspond to score needs in SAT/IELTS, respectively. National trends and equivalency cohort composition, in combination, draw attention to the significance of specifying means by which supports for learning, such as AI, can promote increased engagement, persistence, and achievement for different types of students.

III. RESULTS

The demographic characteristics are (1) gender, (2) age, (3) department/field, and (4) How many years are you studying in Table II.

TABLE II. DEMOGRAPHIC PROFILE OF RESPONDENTS

Gender	Frequency	Percent
Female	110	72.85%
Male	41	27.15%
Total	151	100%
Age	Frequency	Percent
18-28	147	97.35%
29-44	4	2.65%
Total	151	100%
Department	Frequency	Percent
Business Administration and Management	146	96.69%
Engineering	1	0.66%
Other	4	2.65%
Total	151	100%
How many years are you studying?	Frequency	Percent
Freshman and Sophomore	62	41.06%
Junior and Senior	89	58.94%
Total	151	100%

Exploratory Factor analysis

An exploratory factor analysis (EFA) was conducted on the 52 indicators of ChatGPT use's influences on the

academic achievement construct. Sampling adequacy was adequate (Kaiser–Meyer–Olkin, KMO = .872) and Bartlett's test of sphericity confirmed to us that the correlation matrix was good to support factoring, $\chi^2(561) = 3,188.958$, $p < .001$. These diagnostics thus warranted proceeding with factor extraction. The six-factor solution retained (with criteria as specified) mapped to the theorized sub-dimensions and accounted for 74.977% of the total variance (cumulative), illustrating that the postulated structure shares an adequate proportion of common variance between the items, and, in consequence, captures an obvious and cohesive subset of interrelated items. Item–factor assignments adhered to the conceptual model, in which each item demonstrated its largest loading on the intended latent dimension and showed minimum cross-loadings.

TABLE III. KMO AND BARTLETT'S TEST

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.872
Bartlett's Test of Sphericity	Approx. Chi-Square	3188.958
	df	561
	Sig.	.000

Measurement Model and Structural Modeling

Before estimating the structural relations, the reliability and validity of measurement models were tested. Internal consistency was assessed based on Cronbach's alpha (α) as follows: if $\alpha \geq .70$, then it was deemed to be acceptable; otherwise, it was not. Convergent validity was estimated based on standardized factor loadings (λ), composite reliability (CR), and average variance extracted (AVE) based on common cutoffs of $\lambda \geq .70$, $CR \geq .70$ –.80, and $AVE \geq .50$, respectively. Discriminant validity also needs to be evidenced by the Fornell–Larcker criterion (inter-construct correlation being exceeded in their square root terms' estimation by AVE's square root) and the HTMT ratio being below recommended cutoffs.

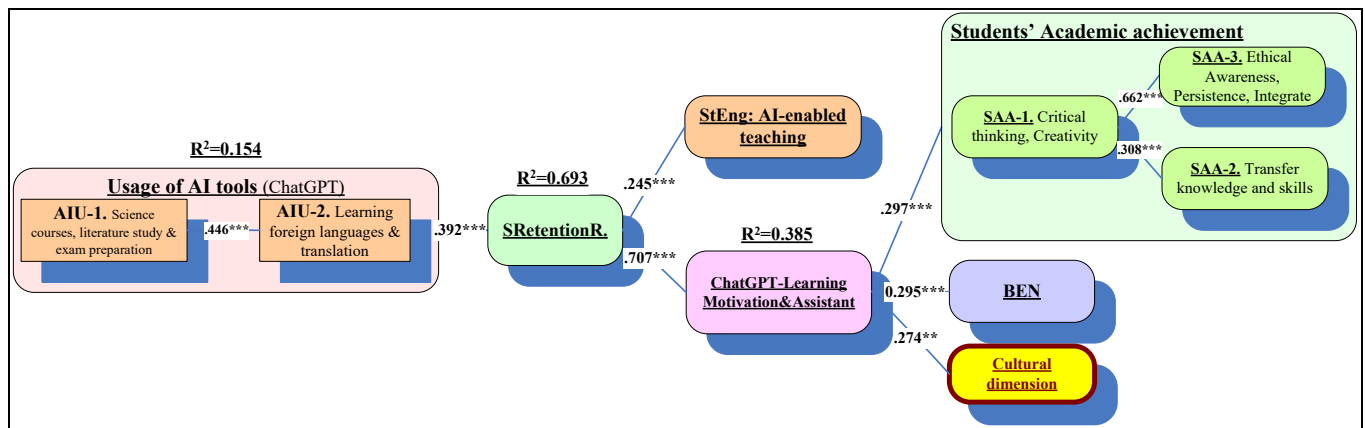
Table IV shows measurement statistics (std loadings, α , CR, AVE) of each sub-dimension. The measurement characteristics provide the base to estimate the structural equation model (SEM) of AI-related perceptions and outcomes; model fit indices can then be reported along with estimates of structural paths.

TABLE IV. RELIABILITY AND CONVERGENT VALIDITY OF THE MEASUREMENT MODEL (LOADING, CR, AVE, AND CRONBACH'S ALPHA.)

Factor	Variables	Loadings (λ)	Cronbach's α	CR	AVE
SAA-1. Critical thinking, Creativity			0.895	0.882	71%
SAA-05.	SAA-1. Critical thinking, Creativity	.865			
SAA-08.		.849			
SAA-04.		.819			
SAA-2. Transfer knowledge and skills			0.893	0.820	60%
SAA-02.	SAA-2. Transfer knowledge and skills	.793			
SAA-01.		.769			
SAA-03.		.765			
SAA-3. Ethical Awareness, Persistence, Integrate			0.866	0.827	61%
SAA-07.	SAA-3. Ethical Awareness, Persistence, Integrate	.815			
SAA-06.		.799			
SAA-09.		.734			
SRR-Students' Retention and Recommendation system			0.913	0.883	60%
SRR2.3	recommends trustworthy educational resources to me.	.806			
SRR2.1	provides me more control over my exploration in learning.	.787			
SRR1.2	preventing me from dropping out of my	.772			

SRR1.3	can help me develop habits to stay focused on my learning.	.769			
SRR2.2	provides suggestions about my learning that can save me time.	.741			
LearnMotiv-Learning Motivation			0.872	0.802	57%
LMot3	AI has made a valuable contribution to improving my academic performance.	.794			
LMot1	Using AI tools has strengthened my motivation to learn.	.770			
LMot2	AI tools are my most effective learning assistant.	.708			
CULT- Cultural dimension			0.893	0.903	61%
ShTO-02	Social responsibilities should be fulfilled at all costs.	.836			
UAI-01	Uncertainty is a normal part of life and may occur on a daily basis.	.811			
LTO-02	People should be persistent and persevering in pursuit of long-term outcomes.	.781			
FEM-01	Caring for and protecting others is a dominant social value.	.777			
COL-01	Loyalty can broaden and strengthen one's ties with one's family and in-group.	.747			
ShTO-01	Traditions ought to be respected	.722			
AIU-1. Usage of AI tools (ChatGPT)			0.839	0.859	60%

AIU-11	How often do you use ChatGPT for your science courses?	.810			
AIU-09	use ChatGPT for your math. and statistics courses?	.809			
AIU-06	research and literature study	.749			
AIU-02	exam preparation	.740			
AIU-2. Usage of AI tools (ChatGPT)			0.805	0.758	61%
AIU05.	use ChatGPT for translation tasks and for learning foreign languages?	.818			
AIU18.	translations	.744			
BEN-Benefit			0.861	0.862	67%
Ben01	ChatGPT saves time	.848			
Ben1.2	reduces study hours by 50%	.817			
Ben1.1	saves time by quickly synthesizing broad topics upon request	.799			
StEng: AI-enabled teaching & management			0.919	0.718	56%
StEng02.1	AI is better than a human teacher for taking attendance.	.762			
StEng02.2	If courses were taught with the help of AI, they would be much better than those taught by a human teacher alone.	.735			



* p < 0.05 ** p < 0.01 *** p < 0.001

Fig. 1. Structural model.

IV. CONCLUSIONS AND RECOMMENDATIONS

In this study, we explored the impact of artificial intelligence, i.e., ChatGPT, on students' academic achievement at the university. Focusing on a sample of 151 students from the department of Business and Management, we revealed the evidence that the use of ChatGPT could positively impact determinative factors influencing students' academic achievement. The results, in aggregate, show that students' ChatGPT use explained 69.3% of the variance in student retention/dropout ($R^2 = .693$). The latter, in turn, due to improved focus, persistence, and active engagement, explained 38.5% of the variance in learning motivation ($R^2 = .385$). Increased motivation, in turn, related positively to a number of dimensions of academic achievement—creativity and critical thinking, ethical awareness, and knowledge/analysis transfer.

Accordingly, the successful infusion of AI into learning also demands prudent treatment of the challenges. Our analysis saw the concerns of over-reliance on AI, the spotty veracity of the information presented by AI, and the irreplaceable character of human interaction. These cautions signal that the intended positive impacts observed would come into full bloom only in a scenario under which AI would be used prudentially and as part of a balanced approach to learning.

The limitation of research. First, our sample included primarily management students from a single university, which might limit generalizability. Different subjects might

employ the tools of AI differently (e.g., students of coding might employ the tools of AI differently from management students), and student sentiment about AI may differ between cultures or between education systems. Second, our academic success metric depended on student self-report (perceptions of improvement, self-reporting of GPA, etc.), which might be biased. Our academic success metric depended on student self-report (perceptions of improvement, self-reporting of GPA, etc.), which might be biased. Third, the rapidly changing character of the technology of AI means research quickly goes out of date. The technology of ChatGPT itself keeps evolving, and new tools of AI continue to emerge; consequently, repeated research becomes necessary in order to trace the impact that these developments leave on education. Fourth, the culture-sensitive analyses are exploratory ones: the short cultural items were not validated at the local level, measurement invariance across subgroups was not investigated, and—analogueous to the Hofstede platform's differentiation between validated national scores and non-validated guesstimates—we do not provide numeric Hofstede values for Mongolia and do not infer with non-validated ones. Future research must (i) conduct longitudinal and randomized studies; (ii) combine self-reports with behavioral and administrative records; (iii) assemble multi-institutional and cross-national samples; and (iv) use validated cultural measures relevant to the Mongolian situation (or other frameworks) in conjunction with explicit tests of measurement invariance, with preregistered, hypothesis-driven tests of culture–AI mechanisms [10], [11].

The research supports the general need for innovation in learning through technology, as it shows the potential for AI as a catalyst for more interactive and adaptive learning. But for all these gains to be achieved and for AI to positively impact academic achievement sustainably, it must be incorporated carefully. Accordingly, from the research results and the arguments presented herein, the following recommendations for educational practice and policy are proposed:

1. Strategic use of AI for the improvement of learning and teaching (example: closing and eliminating this knowledge gap for students with limited skills and knowledge): Teachers must incorporate AI tools like ChatGPT into their curriculum for strategic use. Rather than banning or doing without them, teachers might employ them as a supplement for the traditional approach. One may, for instance, use ChatGPT for the development of practice questions, receiving instant comments for a draft, or as a conversational partner for developing ideas. The use of AI for class activities (like peer-review activities through the use of AI-produced comments or research assignments supported by AI) might increase participation. The emphasis lies in the combination of AI for learning, i.e., by employing ChatGPT for the reinforcement of concepts taught during class, not by circumventing the learning process.
2. Direction and Training for the Efficient Use of AI: Colleges must develop guidelines and training programs for students as well as teachers for the effective and ethical use of AI for academic work. As students get training for the use of the library or the online databases, they also require training for the use of AI tools online. This could include workshops for the crafting of effective prompts for preferred responses from AI, training for the critical evaluation and fact-checking of AI-generated content, and defined policies for acceptable use of AI for assignments.
3. Stress Critical Thinking and Human Supervision: As a means of keeping students from becoming overly dependent upon AI, teachers must continue to stress critical thinking and problem-solving. Students can first be asked to work without the involvement of AI, then use ChatGPT for the purposes of verifying or enhancing understanding, and finally, for critical examination of any submitted AI. Activities may be set up for the class such that students debate why an AI solution is correct or incorrect as a means of exercising the students' own thinking skills.
4. Development of Policies and Ongoing Assessment: Educational institutions and governing boards must develop particular policies when addressing the use of AI in teaching. The policies could involve academic integrity (such as the necessity for disclosure of the use of AI support when submitting assignments), data protection issues when students use AI platforms, and the extent to which AI might feature during assessment. Formal guidelines will codify practice and give anticipated expectations for staff and students. Institutions must also regularly review the effects of the inclusion of AI. This could involve collecting feedback every semester as to how AI tools affected learning, monitoring trends in

academic performance over the long term as AI usage increases, and conducting other research studies.

Adopting these guidelines, education stakeholders would better handle the adoption of AI tools like ChatGPT into the classroom. In conclusion, ChatGPT and other tools for artificial intelligence hold immense promise for student academic achievement, but reaching this potential in full will depend on cautious use, informed by research and moderated by the proven adages of effective learning and instructing.

Cultural dimensions (exploratory and hypothesis-generating). The found relationships between achievement-related outcomes and a series of self-selected cultural value orientations (e.g., deference to tradition, weaker uncertainty avoiding, in-group loyalty, long-term staying power, concern for others) were small and had been estimated with restricted precision. Considering our cross-sectional design, self-reports, single-site sample, and given that the Hofstede platform differentiates between a validated national scores and a non-validated guesstimates—not recommended by it for scientific inference—we do not provide numeric Hofstede scores for Mongolia and consider here these findings as preliminary [H1], [H2]. As a result, we provide the following testable hypotheses for future confirmatory work:

- H1. Lower uncertainty avoiding will be positively related to the width and depth of AI-augmented learning strategies.
- H2. Long-term orientation will have a positive association with long-term, goal-oriented interaction with AI resources with time.
- H3. Prosocial orientations for value (e.g., protecting others; loyalty to the in-group) will be positively related to ethical concern in AI-augmented student work.

High-powered tests must employ multi-site samples, longitudinal or experimental designs, and measurement-invariance tests for cultural scales, along with proven cultural metrics available [H1], [H2].

In a Mongolian university setting, self-reported use of ChatGPT was positively associated with student retention and learning motivation, which in turn correlated with multiple dimensions of academic achievement (critical/creative thinking, ethical awareness, and knowledge transfer). These findings should be interpreted cautiously..

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