Gendered Patterns of Generative AI Adoption among University Students: A Cross-Cultural Survey of Chinese and International Users

Jiong Li[a]

King's College London University College London, "Department of Culture, Media & Creative Industries, Institute of Education, UCL", London, United Kingdom

[a]qtnzjl8@ucl.ac.uk

Abstract

The fast spread of generative artificial intelligence has already become pervasive in university students' media practices, but there is still an inadequate understanding of the gender and culturally embedded factors underlying its adoption process. This paper examines the effect of gender and cultural background in isolation and combination on the frequency, diversity, and types of generative AI adoption by university students in China using a cross-cultural online survey of 412 respondents, including both Chinese students and students of other countries. As shown, statistically significant gender differences occur on all three dimensions – male respondents have more frequent AI use and greater use diversity, with a notable inclination toward AI coding help and entertainment purposes, whereas women are mainly engaged in AI academic writing and language translation. From a two-way analysis of variance (ANOVA), gender and cultural background interact to produce a significant small effect size (η_p^2=.011), where the gender difference among international students is larger than that of Chinese students (mean difference=0.61 vs. 0.26). Regression analysis also supports the significance of both predictors with a negative interaction coefficient (β=-.15, p=.038), which implies that Chinese cultural orientation reduces gender differences. In all, the results provide a broader understanding of gender digital divide by shifting the discussion from the access stage to the usage stage, indicating that AI technology's institutionalization and the features of the domestic platform ecosystem might partly explain the gender divide in China.

Keywords

Gender, generative AI, media practice, cultural context, cross-cultural communication, university students.

1. Introduction

Generative artificial intelligence technologies have come to radically transform higher education media practices as never before experienced before. Technologies like ChatGPT, ERNIE Bot, and Midjourney have moved beyond their novelty status and have become indispensable elements of the media ecosystem employed by university students for academic writing, information search, content generation, and multilingual communication. Indeed, findings from a recent large-scale survey conducted at a prestigious liberal arts college in the United States indicate that more than 80 percent of students in this institution had already incorporated the use of generative AI technologies in their academic pursuits within two years after the appearance of ChatGPT on the market, with the prevalence growing from less than 10 percent of respondents prior to Spring 2023 to nearly universal adoption [1]. In a nationwide survey conducted among 1,041 students across universities in the UK, 92 percent stated that they used AI by early 2025, compared with 66 percent in the previous year, with males demonstrating greater interest and frequency [2]. However, all these findings provide a distorted picture of what happens in terms of adoption behavior.

When it comes to the gender aspect, there has been a steady rise in empirical evidence about the existence of gender disparities in terms of generative AI utilization, despite the fact that such observations are still rather qualitative in nature. An analysis of 18 different studies that involved over 140,000 participants from 25 countries found out that, on average, females are about 20 percent less likely to utilize generative AI compared to their male counterparts; and this gap remains virtually unchanged for all countries regardless of the equal availability of the technology [3]. It should be noted that the discovery has great implications in many aspects. Yet, the unit of analysis in most of these cases is simply the fact of using AI or not, while others are not addressed adequately enough.

In terms of cultural factors, gender cannot ever act as a standalone variable in any social context. Gender roles, educational institutions' systems, and digital media ecosystems can be very different in various cultures, which might lead to significantly different patterns of AI usage by the same gender group within different environments. Cross-country statistics showed significant differences in the frequency of AI adoption and attitudes towards AI technologies between the people from Eastern and Western countries. Specifically, the influence of gender on AI adoption might be attenuated by collectivist cultural orientations and institution-driven technology integration characteristic of Eastern culture and institutionally driven adoption practices, whereas a more autonomous attitude in individualistic Western cultures might intensify differences in terms of gender. Still, this moderating effect of culture on gender has not been thoroughly analyzed in generative AI literature to date. Another knowledge gap concerns the absence of generative AI research from other disciplines, specifically from communications studies.

In contrast to these deficiencies, the proposed study asks three research questions that have an increasingly complex structure. Research question one, formulated at the descriptive level, will determine whether there are any significant gender differences regarding the frequency of using generative AI by students, the context of such usage, and their preference in choosing certain tools. Research question two, formulated at the moderating level, will assess whether the role of culture, measured by the difference between Chinese and international students, will moderate gender's impact on the context and frequency of use. Lastly, research question three on a predictive-modeling basis considers the impact of gender and culture on usage diversity, defined as the number of application contexts within which the individual user operates, and tests whether the interaction provides additional variance beyond its components. All research questions utilize a common data set and variables, with the methods increasing from the descriptive level to analysis of variance and, ultimately, to regression models.

2. Literature Review

2.1. Differentiated Adoption of Generative AI in Higher Education

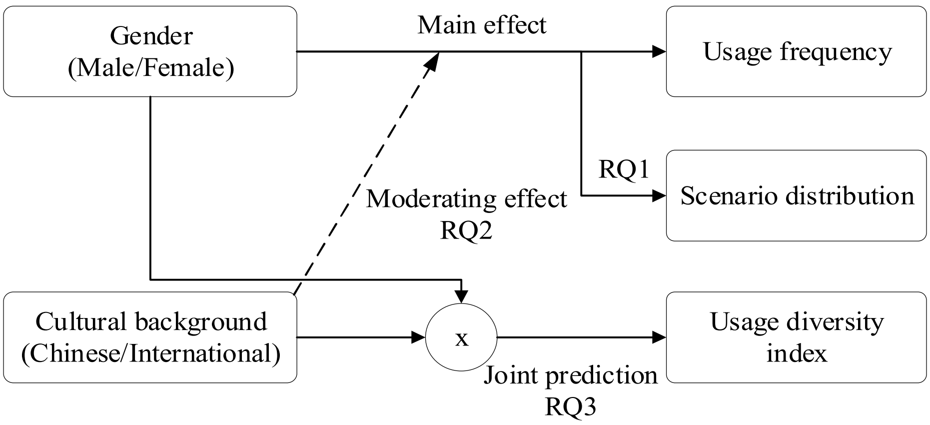
Previous research has offered a necessary empirical foundation to analyze generative AI adoption by university students. The results of a cross-sectional survey of 534 undergraduate nursing students enrolled at a university located in western China indicated that approximately 57.86% of respondents used generative AI products frequently and consistently. The primary scenarios were problem-solving (84.46%) and class-related activities (66.29%). Additionally, the choice of software is highly biased towards domestic services with DeepSeek being the preferred product (72.10%) and Doubao following closely (69.85%) [4]. Such a pronounced pattern of usage has also been confirmed in other surveys involving Chinese users. However, a comparative study analyzing professionals in China and the UK has highlighted the fact that platform accessibility and integration are key factors affecting choice among Chinese users, while usage by British counterparts appears to be much less biased towards domestic products [5]. While the findings presented above provide some insight into the patterns of software usage, none of the works focuses on gender as an essential criterion.

2.2. Gender and Digital Media Use - From the Access Divide to the Practice Divide

The research on the concept of gender digital divide has seen an evolution of three levels of this phenomenon, from the initial first-level division concerned with physical access inequality to the second-level divide based on inequality of usage, up to the third level which emphasizes the differences in usage outcome and digital capital [6]. In the context of generative AI, however, it is still meaningful to look at the multi-layered perspective. Research shows that despite equalization of AI risk understanding owing to technical education, there was a difference in male and female students' willingness to apply AI (3.55 males vs. 3.26 females, $p=.046$) [7]. The cognitive equality with behavioral inequality indicates that gender differences in the usage of AI should be explained by factors beyond mere cognition, such as cultural traditions, social roles, and media habits, rather than by cognitive mechanisms [8]. It turns out, then, that overcoming the knowledge-level gender divide does not necessarily imply overcoming the behavioral divide. Analytically speaking, the attention needs to be drawn away from students' knowledge about AI to their actual use of it.

2.3. Technology Use Behavior from a Cross-Cultural Communication Perspective

A model based on the traditional cultural dimension theory is the first basic resource for studying cross-national differences in technology acceptance behavior by dividing national culture into a number of dimensions, such as power distance, individualism-collectivism, and masculinity-femininity, thus creating the basis for cross-cultural comparison studies [9]. The results of meta-analysis of cross-national empirical data revealed that low masculinity was linked to higher rates of technology adoption, power distance correlated with intention to use technology, while individualism negatively correlated with the willingness to adopt technology [10]. In the context of generative AI, a cross-cultural survey conducted among foreign students in China showed that cultural adaptation, subject field, and perceived usefulness all impact the formation of adoption intention, and this effect had distinct differences among students coming from various parts of the world [11].



Note: Solid lines = direct effect pathways; dashed lines = moderating effect pathways

Figure 1. Analytical Framework of the Study

However, although all of the above-reviewed cross-cultural research includes gender as one of the demographic variables to consider, none focuses on the interaction effect between gender and cultural background as the key factor. This is the very area to which the current research will devote its attention. Instead of focusing on gender and culture independently of each other as predictive factors, an overall analytical structure will be developed where both will serve as independent factors and their impact on three aspects of AI use – frequency, distribution, and diversity – will be studied.

3. Methodology

3.1. Research Design and Sample

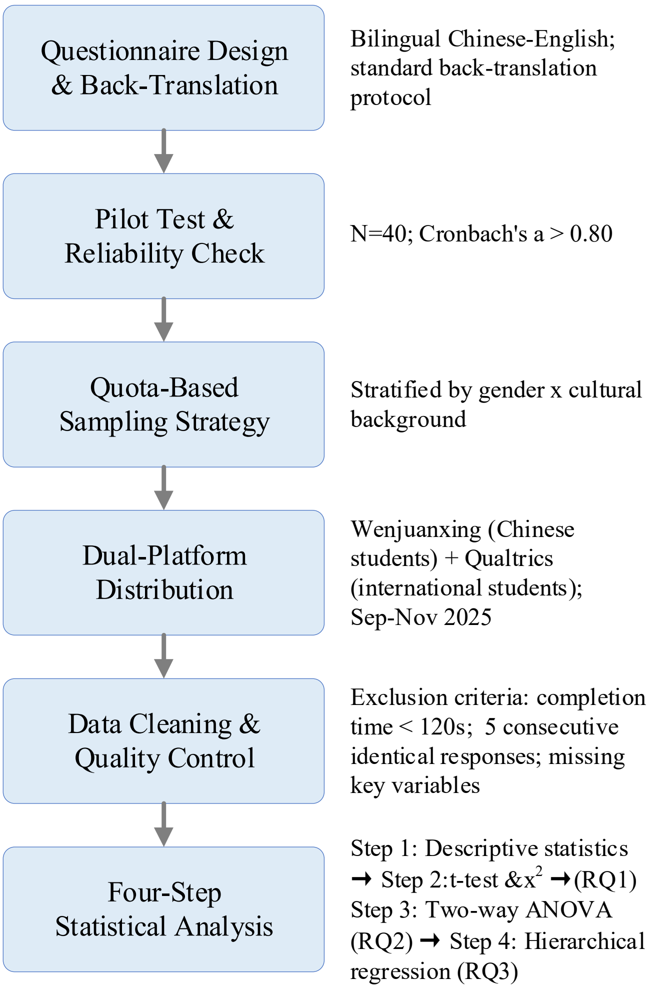


Figure 2. Research Procedure Flowchart

The present study adopted a cross-sectional survey design conducted via the internet and involving current university students enrolled in Chinese universities as well as international students enrolled in foreign universities. In this regard, the questionnaire used for data collection was prepared using both Chinese and English language and back-translated in order to verify the semantic equivalency between the two languages. Accordingly, the Chinese version was sent using Wenjuanxing to three comprehensive universities in eastern, central, and western China, whereas the English version was concurrently sent to four universities in Southeast Asia, South Asia, and Europe using Qualtrics. Quota sampling in which convenience sampling was coupled with stratification by gender and culture served as the sampling technique used. The eligibility criterion consisted of being 18 years old and above and currently studying in a university program. Approximately 8 weeks were taken to collect the required data between September and November 2025. Approval to conduct the research was sought from the concerned institution's ethics committee. Participation in this study was voluntary and anonymous, and all participants were made aware of the purposes of this study as well as the withdrawal policies before conducting the survey; starting the process equated to informed consent.

The total number of participants in the study from both online forums is 486. After conducting a data cleaning exercise where entries having time less than 120 seconds (n=27), more than five same responses in a row (n=31), and missing responses for important variables (n=16) were discarded, the resulting dataset contained N=412 valid entries, giving an overall response rate of 84.8%. The respondent characteristics are displayed in Table 1.

Table 1. Demographic Profile of Respondents (N=412)

Variable	Category	n	%
Gender	Male	191	46.4
	Female	221	53.6
Cultural background	Chinese students	209	50.7
	International students	203	49.3
Region of international students	Southeast Asia	68	33.5
	South Asia	47	23.2
	Europe	39	19.2
	Africa	31	15.3
	Other	18	8.9
Education level	Undergraduate	274	66.5
	Postgraduate	138	33.5
Duration of AI use	≤6 months	105	25.5
	7–12 months	148	35.9
	>12 months	159	38.6

The ratio between males and females approached 1:1, while that of the Chinese to the international students was almost identical. The regional background of the international students was considered and classified as being from Southeast Asia, South Asia, Europe, Africa, and other areas, as a way of dealing with validity issues associated with using international students as one homogenous group. Cultural background was used as a categorical variable with only two categories-either Chinese or international-in the analysis of variance test.

3.2. Variable Measurement

The measurement tool consisted of six key independent variables. The fact that the dependent variables were either single variables (usage frequency, preference of tool) or an index variable generated from a simple yes/no checklist (Usage Diversity Index) made it inappropriate to calculate conventional internal consistency reliability coefficients. Eight-item usage scenarios and the whole measurement tool were pilot tested on a convenience sample of forty respondents, with no need for any revisions to the items.

The frequency of use of the technology was chosen as the first dependent variable and measured as the number of times during the last month the participant used generative AI in any form, using a Likert scale (1=never; 5=several times per day). The mentioned frequency served as the basis for the RQ1 and RQ2 analysis.

Scenario frequency distribution was a multiple response variable, and the respondent had to choose several items out of eight predefined options related to the usage (academic writing, research and information gathering, content creation, programming help, translations, conversations, social media posts, and entertainment).

The Usage Diversity Index emerged as one of the most significant components of the research design. The index resulted from the number of scenarios chosen by respondents in the case of the multiple-choice task; thus, the resulting index varied between 0 and 8, and there was no need to use a particular scale in this instance since the variable could be used as the dependent variable in RQ3.

The preference for an artificial intelligence tool was determined using the single choice question with four possible types of AI tools (text generation, image generation, coding assistance, and multi-function tools). This was done in order to compare different preferences according to RQ1.

In terms of independent variables, two of them were considered – gender and cultural background. Gender could be defined by choosing either male or female in the questionnaire. Concerning cultural background, two categories were established (Chinese=1, international=0).

3.3. Data Analysis Strategy

Data analysis followed a four-step hierarchical strategy aligned with the three research questions.

The initial step was calculating descriptive statistics such as means, standard deviations, and frequencies for all variables, so that the baseline AI usage profile could be constructed among the entire sample. In Step 2, addressing Research Question 1, t-test procedures were used to detect mean differences between male and female students regarding their frequency of using AI as well as their use of diverse types of AI. As for usage scenarios, a multiple response variable, chi-square tests for each scenario were performed since these categories were not mutually exclusive. For tool preference, which was a single-choice categorical variable with four mutually exclusive options, a single chi-square test was performed on the 4×2 contingency table. The distribution of this variable was further investigated through adjusted standardized residuals (ASR). Step 3 addressed Research Question 2 by performing 2×2 two-way ANOVAs, in which main effects of gender and cultural background as well as their interaction effect were tested on the dependent variables – frequency of using AI and the Usage Diversity Index. Simple effect analysis was done in the presence of interaction. Step 4, concerning Research Question 3, consisted in hierarchical multiple linear regression in which Model 1 entered gender and cultural background as main effect predictors, while Model 2 added an interaction between gender and cultural background as predictor. The difference in R^2 change (ΔR^2) accounted for the interaction effect in the regression. The dependent variable in the regression was Usage Diversity Index, continuous (from 0 to 8). Gender and cultural background were included into the regression equation using dummy coding technique. All data processing was done in SPSS 27.0; significance level was set at $p < .05$.

4. Results

4.1. Overall Profile of Generative AI Usage

Among the total of 412 participants, 89.3% (n=368) have indicated their experience in using any AI technology within the past month. The mean frequency of usage among all respondents amounted to 3.42 (SD=1.10, five-point Likert scale), which equals to usage multiple times a week. Text generation tools represented the biggest percentage of technology preferences (61.2%), while multifunction tools came second (19.7%). After that followed image generation tools (12.1%) and coding assistance tools (7.0%). The three most frequently addressed scenarios of use were those related to academic writing (78.6%), searching information (71.8%), and translating languages (54.1%). However, coding assistance (22.6%) and leisure purposes (31.1%) were not as popular among respondents. The mean value of the Usage Diversity Index equaled 3.86 (SD=1.62, range 0-8).

4.2. Gender Difference Analysis (RQ1)

Independent-samples t-tests and chi-square tests revealed significant gender differences across multiple dimensions of generative AI usage (see Table 2).

Table 2. Gender Differences in AI Usage Patterns

Indicator	Male (n=191) M(SD)	Female (n=221) M(SD)	t/χ^2	p
Usage frequency	3.67 (1.04)	3.21 (1.07)	t=4.36	<.001
Usage Diversity Index	4.18 (1.55)	3.58 (1.61)	t=3.80	<.001
Tool preference (overall 4×2)	-	-	$\chi^2(3)=13.32$	.004

The male group used generative AI significantly more often (t=4.36, p<.001) and had a significantly larger variation in terms of usage (t=3.80, p<.001) compared to the female group, Mdifference=0.46, Mdifference=0.60. This result suggests that males tended to use generative AI in a wider variety of situations. As for the preference of different types of AI tools, a chi-square test performed on the 4×2 table showed a significant association between the gender and tool category preference (χ^2(3, N=412)=13.32, p=.004, Cramér's V=.18). According to the adjusted standardized residuals' analysis, gender differences existed only in two categories – females used text generation tools significantly more often (67.0% vs. 54.5%, ASR=2.60), whereas males opted for coding assistance tools significantly more often (11.5% vs. 3.2%, ASR=3.31). No statistically significant gender differences appeared in the usage rates of image generation and multi-function tools.

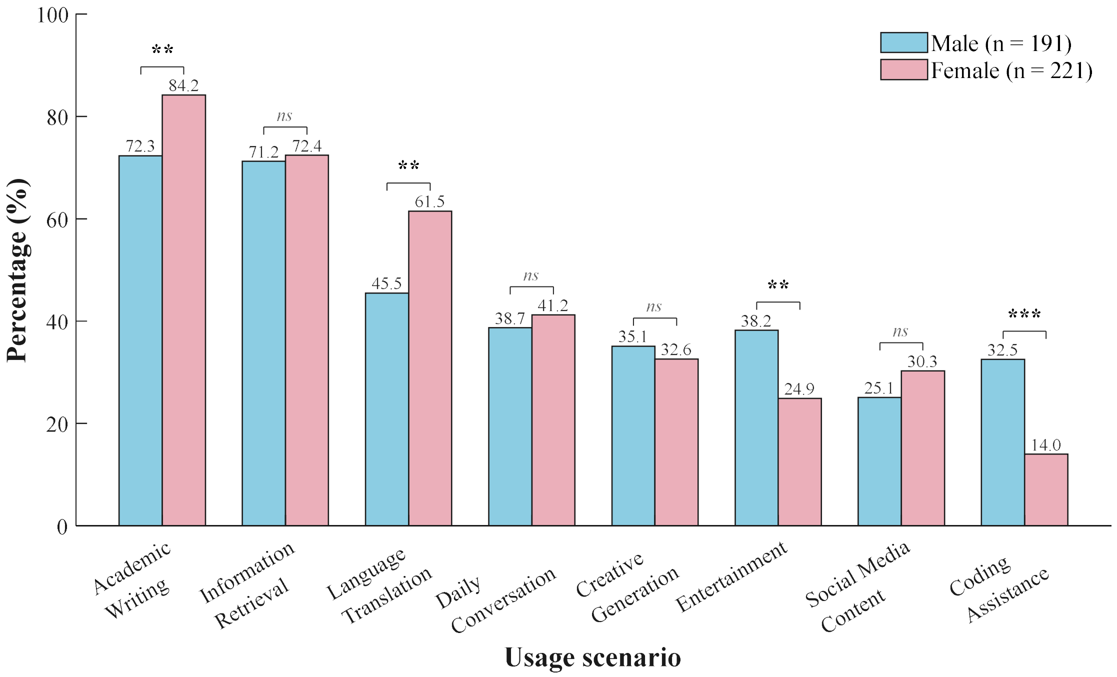


Figure 3. Gender Differences in Usage Scenario Distribution

Note: **p < .01; ***p < .001; ns = not significant (p ≥ .05). Chi-square tests were used for all comparisons.

Gender differences in the distribution of scenarios are also illustrated in Figure 3. The use of scenarios for coding assistance was higher for males (32.5%) compared to females (14.0%), χ^2 = 19.87, p < .001, and the same can be said about the use of the entertainment scenario (38.2% vs. 24.9%, χ^2 = 8.54, p = .003). Females reported significantly higher usage rates for scenarios in academic writing (84.2% vs. 72.3%, χ^2 = 8.80, p=.003) and language translation (61.5% vs. 45.5%, χ^2=10.56, p=.001). Notably, the creative generation scenario yielded no significant gender difference (35.1% vs. 32.6%, χ^2=0.29, p=.591).

4.3. Moderating Effect of Cultural Background (RQ2)

A 2×2 two-way ANOVA with gender and cultural background as fixed factors and AI usage frequency as the dependent variable yielded the results presented in Table 3.

Table 3. Two-way ANOVA Results for AI Usage Frequency

Source	SS	df	MS	F	p	η_p^2
Gender	18.72	1	18.72	16.53	<.001	.039
Cultural background	6.85	1	6.85	6.05	.014	.015
Gender × Cultural background	5.24	1	5.24	4.63	.032	.011
Error	462.05	408	1.13			

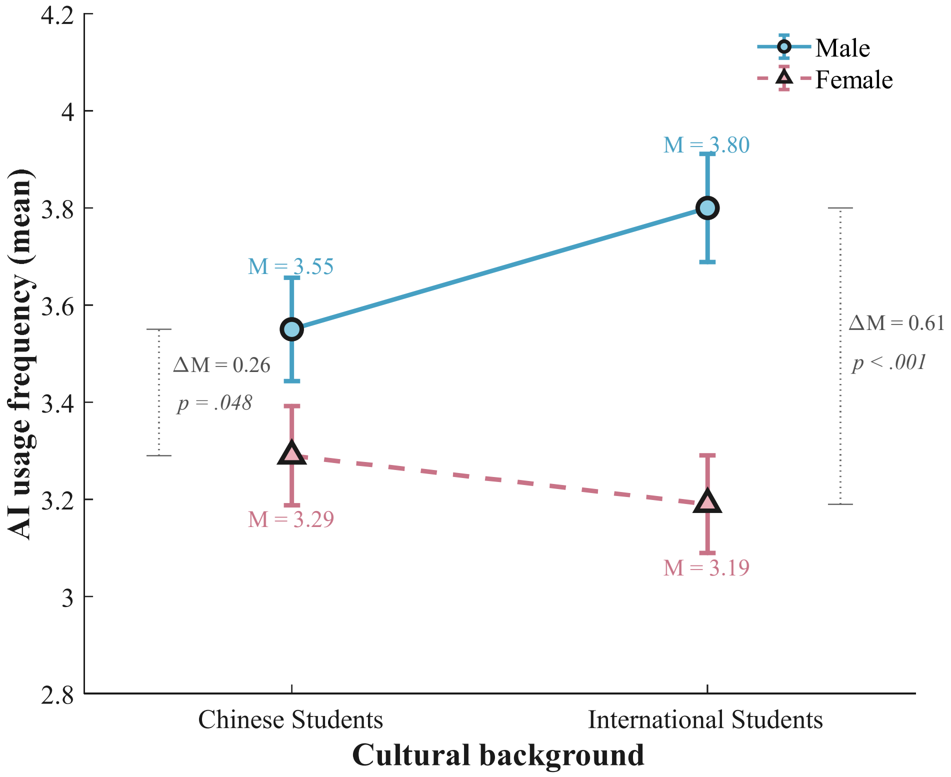


Figure 4. Interaction of Gender and Cultural Background on AI Usage Frequency

Gender emerged as a significant factor for the effect under consideration (F(1,408)=16.53, p<.001, η_p^2 =.039). Cultural background turned out to be a significant factor as well (F(1,408)=6.05, p=.014, η_p^2=.015). The ANOVA also detected a statistically significant, though small in magnitude, interaction between the two factors (F(1,408)=4.63, p=.032, η_p^2 =.011). Simple effects analysis showed that, among international students, the use frequency for males was significantly greater compared to that for females (M difference=0.61, p<.001). At the same time, although males also made significantly more use than females among Chinese students (M difference=0.26, p=.048), the gap was substantially narrower than that observed in the international group.

Similarly, an ANOVA analysis with parallel two-way ANOVA model for the Usage Diversity Index revealed the presence of significant interaction ($F(1,408)=4.11$, $p=.043$, $\eta_p^2=.010$). Again, it is similar to frequency where gender difference in international students is higher than in the Chinese students' group.

4.4. Joint Prediction of Usage Diversity by Gender and Cultural Background (RQ3)

The results of hierarchical multiple linear regression are presented in Table 4.

Table 4. Hierarchical Regression Results for Usage Diversity Index

	Model 1 (main effects)	Model 2 (with interaction)
Variable	β	β
Gender (female=0, male=1)	.19 (<.001)	.28 (<.001)
Cultural background (international=0, Chinese=1)	.11 (.021)	.18 (.004)
Gender × Cultural background	—	-.15 (.038)
R^2	.053	.064
ΔR^2	—	.011 (p=.038)
F	11.38 (<.001)	9.30 (<.001)

With regard to Model 1, both gender (β=.19, p<.001) and cultural background (β=.11, p=.021) emerged as statistically significant positive predictors of usage diversity, explaining 5.3% of the variance. However, the introduction of the gender × cultural background interaction in Model 2 led to an increase in the proportion of variance explained by $\Delta R^2=.011$ (p=.038). Specifically, the standardized regression coefficient of the gender × cultural background interaction was -.15, suggesting that a Chinese cultural background reduced the predictive efficacy of gender on usage diversity. The interaction term's direction and significance were in alignment with each other across both ANOVA and regression approaches, which is evidence of cross-verification between the two methods. What must be pointed out is the fact that the estimates from both analyses are not adjusted values; neither educational attainment nor AI usage time was included as a covariate, and the categorical variable for the students' cultures inherently includes other variables like language setting, accessibility to platforms, and institutions' policies. Thus, one can say that there is variability in the association between gender and usage in the two groups.

5. Discussion

This paper used survey data from 412 Chinese and international university students to analyze the independent and joint influences of gender and culture on generative AI usage behavior.

The findings revealed that gender played an important role in generative AI use behaviors and had a multidimensional influence on generative AI usage practices, corroborating previous global gender gap studies. What is valuable about this study is its nuanced approach at the level of use, beyond a binary analysis of use or no use. On the scenario level, the concentrated advantages held by males in coding and entertainment reveal the existence of gender scripts in traditional technology culture that encourage men to use technology in an instrumental way [12]. On the other hand, the fact that females were inclined to use generative AI for academic writing and translation indicated that female use behavior is motivated by the logic of completing routine assignments through AI. More interestingly, in creative generation, gender difference was insignificant, which challenged the stereotypical perception of women rejecting technology altogether. This means that some functionalities in AI that facilitate creative behaviors may serve as gender-equitable space.

From the interaction effects analysis, it became evident that the gender gap between Chinese students was smaller than that among international students in terms of both usage frequency and diversity, albeit having a very low effect size (η_p^2 =.011). There appear to be two institutionalized contexts that could explain such an observation. First, there are the institutions of Chinese higher education, which include not only compulsory use but also platform integration of the AI tools in the teaching process and the development of AI literacy programs on university campuses that could give female students some structural access independent of their will, thus minimizing the gender gap. A second possible mechanism is the internal structure of the domestic AI platform landscape of China, which will be covered in the following section. To resort to cultural collectivism as a reason why the gender gap is narrowed among Chinese students is to assume something about the nature of the international population as well, given the share of collectivist-oriented cultures in it: Southeast Asia and South Asia constitute 56.7% of the total. In other words, if collectivism was indeed the driving force behind minimizing the gender gap, then the gap should have been even smaller for this sub-sample of the data.

The analysis results of the regression provided additional evidence of the moderation mechanism. The negative value of the interaction term (β = -.15) supports the theory that an education setting within China would have less of a gender difference regarding usage breadth; however, it must be remembered that this beta coefficient is not adjusted for other variables. In terms of media practices, this similarity may be due to the specific features of China's national AI platform ecosystem, whose representative examples include, first of all, Doubao, ERNIE Bot, and DeepSeek, using highly advanced multi-modal architecture, including natural language generation, information search and coding, as well as creative content creation [5][13]. Such consolidation of functions helps lower the technological entry barrier and contributes to usage homogeneity between genders. Variance explained is still relatively low (R^2=.064), which means that current results can only be seen as providing the evidence of directions and statistical significance of gender-culture interaction rather than predicting its effects comprehensively.

From a theoretical perspective, the contribution is associated with the advancement from treating gender and cultural background as individual control variables to the analysis of their interactive influence on the variable under study. From the practical perspective, the research suggests that gender differences in motivations are likely to have educational relevance, particularly regarding international students, while the Chinese experience in implementing AI technologies in curricula may be replicated elsewhere [14].

6. Conclusion

A survey of 412 Chinese and international university students was conducted to investigate the impact of gender and cultural background on the behavior of users towards generative AI. Several findings indicated considerable gender differences in terms of generative AI usage in different qualitative ways – male students preferred generative AI for help in coding and entertainment purposes, and female students used it more frequently for academic writing and language translation, with no substantial differences between male and female students regarding creative generation. The cultural background played a significant role in the variation of the gender gap, with the former being smaller for Chinese students compared to international students. The integration of AI technologies into China's higher education system and features of the native platform ecosystem have been identified as potential contributors, but the limited impact of these elements must be taken into account. Regression analysis verified the combined effect of gender and cultural background on the generative AI usage behavior in a student population through negative interaction term which coincided with the results of ANOVA. Limitations of this research include convenience sampling leading to a threat to external validity; cross-sectional design prohibiting causality inference; insufficient size of international sub-groups preventing inter-cultural comparison; self-report nature of measurements susceptible to social desirability bias; and the binary operationalization of gender precludes examination of non-binary identities. The hierarchical regression model used only gender and culture as independent variables without including the education level and duration of usage of AI. This was mainly due to the limited scope of the conference paper, but any subsequent research work that aims to replicate the study should consider these factors when running regressions. Future research should include longitudinal designs; disaggregation of the international category into distinct cultural groups; introduction of covariates such as educational background and self-efficacy with AI software; and conduct qualitative interviews about personal user experience with AI.

References

[1] Contractor, Z., & Reyes, G. (2025). Generative AI in higher education: Evidence from an elite college. *IZA Discussion Paper*, No. 18055.

[2] Freeman, J. (2025). *Student Generative AI Survey 2025* (HEPI Policy Note 61). Higher Education Policy Institute.

[3] Otis, N. G., Delecourt, S., Cranney, K., & Koning, R. (2024). Global evidence on gender gaps and generative AI. *Harvard Business School Working Paper*, No. 25-023.

[4] Zhao, Y., Yuan, Y., Wen, Z., Leng, L., Shi, L., Hu, X., Wei, X., Zuo, M., Mou, J., Luo, Q., Chen, M., Hu, R., & Gao, H. (2025). The current status, knowledge, attitudes, and challenges of generative AI use among undergraduate nursing students. *Frontiers in Public Health*, *13*, 1648416.

[5] Wang, S. J. (2026). A comparative analysis of generative AI adoption among design professionals in China and the United Kingdom. *Humanities and Social Sciences Communications*, *13*, Article 411.

[6] Peláez-Sánchez, I. C., Velarde-Camaqui, D., & Ramos-de-Luna, I. (2023). Gender digital divide in education 4.0. *Future in Educational Research*, *1*(1), 12–28.

[7] Yu, S., Carroll, F., & Bentley, B. L. (2026). Rethinking AI literacy education in higher education. *Social Sciences & Humanities Open*, *13*, 102751.

[8] Horvát, E.-Á., & González-Bailón, S. (2024). Quantifying gender disparities and bias online. *Journal of Computer-Mediated Communication*, *29*(1), zmad054.

[9] Hofstede, G. (2011). Dimensionalizing cultures: The Hofstede model in context. *Online Readings in Psychology and Culture*, *2*(1), 8.

[10] Jan, J., Alshare, K. A., & Lane, P. L. (2024). Hofstede's cultural dimensions in technology acceptance models: A meta-analysis. *Universal Access in the Information Society*, *23*, 717–741.

[11] Cao, K. (2026). A cross-cultural study on the adoption intention of generative AI among international students in China. *Frontiers in Education*, *11*, 1833616.

[12] Simões, R. B., Amaral, I., Flores, A. M. M., & Antunes, E. (2023). Scripted gender practices: Young adults' social media app uses in Portugal. *Social Media + Society*, *9*(3).

[13] Cao, K., Wang, P., & Zhao, J. (2025). The moderating role of ethnic culture on adoption intention of generative AI among university students. *Frontiers in Education*, *10*, 1622620.

[14] Gonzales, S. (2024, August 6). AI literacy and the new digital divide: A global call for action. UNESCO Global AI Ethics and Governance Observatory. https://www.unesco.org/ethics-ai/en/articles/ai-literacy-and-new-digital-divide-global-call-action