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PERCEIVED BENEFITS, RISKS, AND READINESS TO USE ARTIFICIAL INTELLIGENCE IN ACADEMIC ADMINISTRATION AMONG CHINESE LANGUAGE MAJORS

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ABSTRACT

This study examines perceived benefits, risks, and readiness to use artificial intelligence (AI) in academic administration among Chinese Language majors at the University of Foreign Language Studies, the University of Danang. A cross-sectional survey collected 288 online responses, analyzed using descriptive statistics, Spearman's rank correlation, and content analysis of open-ended responses. Students positively assessed the potential for faster access to academic information, reduced waiting times, and monitoring academic progress, with agreement rates of 83.5%, 83.0%, and 82.9%, respectively, among valid responses to each item. At the same time, concerns about inaccurate or outdated information, recommendations unsuitable for individual circumstances, and unfairness arising from biased data were widespread. Of the 288 respondents, 219 were both willing to use AI for straightforward academic inquiries and concerned about inaccurate or outdated information. Perceived benefits were positively correlated with readiness to make academic inquiries and to receive alerts accompanied by explanations. The findings suggest that AI-supported services should incorporate verifiable information sources, data protection, and referral mechanisms to responsible personnel. Conclusions are restricted to the surveyed sample and concern self-reported perceptions and readiness.

Keywords: Artificial Intelligence; Academic Administration; Perceived Benefits; Risk Perceptions; Readiness to use AI.

1 INTRODUCTION

The use of artificial intelligence (AI) in academic administration raises requirements extending beyond the ability of a tool to answer questions automatically, because information about course-registration conditions, academic progress, and programme-completion procedures directly affects students' interests. Guidance delivered quickly is valuable only when it is accurate under the applicable rules and circumstances, while an academic alert should provide a rationale enabling recipients to understand the issue and select an appropriate response. It is therefore necessary to investigate what students expect, which potential consequences concern them, and under what conditions they are ready to use AI in order to design appropriate academic services.

Vietnam's educational digital-transformation policy places learners and educators at its centre. Decision No. 131/QD-TTg calls for greater application of information technology and digital transformation to improve educational and

administrative quality and efficiency, while emphasizing awareness-raising and implementation appropriate to practical circumstances (Prime Minister of Vietnam, 2022). Applied to academic administration, this orientation requires technology choices to be linked to students' ability to complete tasks and the accountability of service providers. Learner assessments reveal requirements not fully captured by technical performance indicators. Research on AI in higher education offers important approaches to technology acceptance but also highlights the need for attention to context, ethics, and methodological quality [2]. Chan and Hu (2023) found favourable attitudes towards generative AI alongside concerns about reliability, privacy, and the consequences of its use. In academic advising, Bilquise et al. [4] found that components commonly used in technology-acceptance models were not uniformly associated with intention to adopt a chatbot. These findings underscore the need to specify what is being evaluated and how it is measured before interpreting a positive response as AI acceptance.

For Chinese Language majors, experience with AI may arise from language learning, translation, or personal information searches, whereas academic administration involves tasks governed by particular procedures, authorities, and conditions. Familiarity with a tool must therefore be distinguished from understanding how that tool contributes to academic administrative tasks. Surveying students across study years within a single major makes it possible to situate their assessments within relatively well-defined tasks, including course selection, monitoring learning outcomes, and handling administrative requests. The field of study defines the case examined here; without a comparison group, it is not treated as an explanation for differences from other majors.

This article analyzes a survey of 288 Chinese Language majors at the University of Foreign Language Studies, the University of Danang, to address three related questions: which benefits do students anticipate and which risks do they identify when AI supports academic administration; how is readiness expressed in particular academic situations; and what service-design requirements follow from these assessments? The analysis focuses on the coexistence of expectations, caution, and readiness, providing empirical grounds for management implications appropriate to the study's scope.

2 THEORETICAL BACKGROUND AND ANALYTICAL FRAMEWORK

In this article, AI in academic administration refers to functions that help students access academic information, consider course or study-pathway options, monitor progress, receive alerts, and resolve training-related requests. The scope includes applications described for students to assess possible future use; therefore, reported readiness does not require prior experience with an official university AI system. Similarly, using an information portal or an online form demonstrates interaction with a digital system but does not, by itself, establish that AI was involved.

The concept of perceived benefits draws on Davis [5] technology acceptance model, in which users evaluate how far a technology may improve their task performance. In academic administration, these benefits are operationalized as faster access to information, less effort spent making repeated inquiries, monitoring deadlines, and receiving recommendations suited to academic circumstances. This approach connects technological evaluations to student tasks while clearly distinguishing anticipated benefits from operational outcomes that have actually been measured. Risk perceptions reflect students' concerns about adverse consequences when AI provides information or recommendations. The risks considered include inaccurate or outdated information, advice unsuited to individual circumstances, unfairness arising from biased data or rules, and fewer opportunities for direct interaction. This definition links risk to task-resolution quality and protection of students' interests, consistent with an approach that considers privacy, trust, transparency, and accountability together in educational data use [6]. Readiness is examined separately for each situation, since seeking information governed by clear rules differs from disclosing personal data or following advice that may affect academic pathways. Soffer and Cohen [7] show that students may have privacy concerns while agreeing to share information for educational benefits and demanding institutional transparency. This finding suggests interpreting readiness alongside its accompanying conditions, while recognizing that the particular considerations must be established through each study's questions and context.

The analytical framework consequently relates perceived benefits, risk perceptions, and readiness to requirements for information verification, data protection, and access to responsible personnel. It is a framework for organizing and interpreting evidence, not a tested causal model. Correlations are examined for indicators with appropriate measurement grounds, while simultaneous readiness and concern are identified from selections made by the same respondents. The term 'conditional readiness to use AI' summarizes a pattern of responses in this sample, with the conditions understood precisely as stated in each survey item.

3 RESEARCH METHODS

A cross-sectional survey was conducted in 2026 using a self-administered Google Forms questionnaire and open-ended questions to provide context for quantitative assessments. The non-probability volunteer sample comprised 288

responses: 53 first-year, 100 second-year, 83 third-year, and 52 fourth-year students. Of these, 269 selected female, 17 selected male, one preferred not to specify, and one did not answer the gender question. Survey instructions described the purpose of the study, voluntary participation, the absence of requests for names or student identification numbers, and the principle of reporting aggregate findings. Responses were coded SV001–SV288 to connect closed and open-ended answers without using participant identities. Record checks identified neither entirely blank entries nor pairs of responses identical across all fields, but the survey method did not allow independent verification of respondents' identities. A participation rate was not calculated because the total number of people invited or exposed to the form was unavailable, consistent with Eysenbach [8] distinction between denominators in online survey reporting.

The main analysis covered six perceived-benefit items (PU1–PU6), four risk items (RSK1–RSK4), and six situation-specific readiness items (RA1–RA6). PU and RA items used five response levels from strongly disagree to strongly agree; RSK items used five levels from not at all concerned to extremely concerned. The response 'K' indicated insufficient information to judge and was kept separate from the scale midpoint. Items addressing AI use for academic matters (USE1–USE5), human involvement, trust conditions, transparency, and privacy were used to contextualize and interpret the three principal domains. Descriptive statistics report the number of valid scored responses for each item (n), mean (M), standard deviation (SD), and number selecting levels 4 or 5. Their percentages use respondents scoring 1–5 on that particular item as denominator; respondent-level joint outcomes use the full sample of 288, as explicitly stated. Neither K responses nor blanks were converted to numerical scores or replaced with means. Presenting scores together with counts, percentages, and item content preserves the meaning of Likert-type data, as recommended by Sullivan and Artino (2013).

The perceived-benefit score was the mean of six PU items for 266 cases with complete valid scores; Cronbach's alpha was 0.852 and corrected item–total correlations ranged from 0.595 to 0.676. The score for academic AI use was similarly calculated from five USE items for 263 cases, yielding alpha = 0.839. These coefficients describe internal consistency but do not replace assessment of the instrument's factor structure or measurement validity [10]. RA items were analyzed separately because they combine different conditions and behaviours; risks were likewise reported item by item without constructing an additional composite score. Associations were examined using Spearman's rank correlation, with observation counts determined from valid data for each pair of variables. The three correlations reported here belong to a set of seven exploratory comparisons in the original study; Holm-adjusted p-values were retained from that entire set of seven tests rather than recalculated using only the three selected results [11]. These analyses identify within-sample associations but do not establish a direction of influence between perceived benefits and readiness. Risk–readiness correlations were not separately tested, so findings concerning their relationship are interpreted descriptively as co-occurrence.

Qualitative analysis drew on open-ended responses concerning benefits, concerns, and conditions of use, organizing their content and comparing it with corresponding quantitative choices. The approach was informed by Braun and Clarke's (2006) thematic analysis: relevant ideas were grouped, reviewed in context, and used to clarify how participants understood the issues. Excerpts are attributed using respondent and question codes: SV-M1 for benefits, SV-M2 for risks, and SV-M3 for conditions of use. These excerpts serve illustrative and explanatory purposes; they are not converted into prevalence estimates or treated as in-depth interview findings.

4 RESULTS

4.1 Expected Benefits for Academic Tasks

Survey participants reported relatively frequent exposure to AI: 269/288 (93.4% of the entire sample) used it at least weekly. However, only 100 (34.7%) rated their knowledge as fairly good or good, whereas 163 (56.6%) rated it as average. Perceived benefits were thus assessed by learners familiar with accessing the technology but differing in self-assessed understanding. General AI-use frequency is treated as background exposure, while the following findings represent expectations concerning specific academic tasks.

Benefits directly related to time and progress attracted relatively high agreement. Faster access to academic information was anticipated by 238/285 (83.5%), reduced waiting and repeated inquiries by 235/283 (83.0%), and monitoring progress and academic milestones by 237/286 (82.9%). These findings suggest that students envisage value in timely task completion and lower effort spent searching for information and contacting staff. Because the statements concerned potential assistance, agreement reflects anticipated benefits, not actual time saved or procedures completed through AI.

Table 1: Perceived Benefits of AI in Academic Administration

Assessment item	n	M ± SD	Levels 4–5, n (%)
PU1. Faster access to academic information	285	4.15 ± 0.75	238 (83.5)
PU2. Reduced waiting time and repeated inquiries	283	4.13 ± 0.80	235 (83.0)
PU3. Consistent information across channels	277	3.99 ± 0.76	211 (76.2)
PU4. Monitoring progress and academic milestones	286	4.10 ± 0.77	237 (82.9)
PU5. Recommendations suited to academic status	288	3.90 ± 0.81	217 (75.3)
PU6. Early identification of support needs	270	4.06 ± 0.83	215 (79.6)

Note. n denotes responses scored from 1 to 5; M, mean; SD, standard deviation. Levels 4–5 indicate agree or strongly agree.

Expectations regarding consistency across information channels and suitability of recommendations were also evident, with agreement rates of 76.2% and 75.3%, respectively. For early identification of support needs, 18 students chose K, more than for any other benefit item; positive scores should therefore be interpreted alongside the number reporting insufficient information to judge. The descriptively lower agreement regarding recommendations tailored to academic status suggests the need to attend to personalization quality, although the available data cannot identify why individual respondents did not agree. Differences between items are therefore not interpreted as statistically tested differences.

Open-ended responses clarify the tasks for which students seek support. SV087 suggested that remote processing could 'save students time and reduce the effort required' (SV-M1), while SV128 mentioned first-year students' need to understand the curriculum and select courses. SV129 emphasized identifying outstanding courses, receiving deadline reminders, and completing the programme towards the end of study. These comments situate anticipated benefits in distinct stages of education and add concrete meaning to the questionnaire responses.

4.2 Risks to Information Quality and Academic Interests

Risk perceptions centred on the possibility that the system might provide information or recommendations unsuitable for students' tasks. Among valid scored responses, 87.0% were concerned or very concerned about inaccurate or outdated information, 89.4% about recommendations unsuited to individual circumstances, and 88.2% about unfairness arising from biased data or rules. A reduction in opportunities for direct communication also concerned 73.9% of valid respondents. These percentages represent consequences students considered when envisaging AI use; they do not measure the frequency or severity of actual incidents.

Table 2: Concern about Risks of AI in Academic Administration

Assessment item	n	M ± SD	Levels 4–5, n (%)
RSK1. Inaccurate or outdated information	284	4.25 ± 0.78	247 (87.0)
RSK2. Recommendations unsuited to individual circumstances	283	4.23 ± 0.73	253 (89.4)
RSK3. Unfairness from biased data or rules	279	4.25 ± 0.72	246 (88.2)
RSK4. Fewer opportunities for direct interaction	276	3.96 ± 0.93	204 (73.9)

Students associated accuracy concerns with whether information complied with university regulations. SV240 wondered, 'I do not know whether the information provided by AI has been verified or whether it complies with university regulations' (SV-M2), while SV261 mentioned the effects of inaccurate or slowly updated information on course registration and graduation requirements. These comments highlight the source, effective date, and applicability of an answer. For time-sensitive tasks, rapid responses must also be supported by evidence adequate for their use.

SV193 described the risk of inadequate personalization as AI 'giving formulaic answers that do not suit a student's particular circumstances' (SV-M2). This comment illustrates a limitation students perceive in pathway recommendations or alerts, since general academic-performance information may omit individual conditions requiring consideration. SV110 meanwhile worried that automated AI responses might make it difficult for students to receive a direct reply from the university (SV-M2). Together, these responses indicate that both information quality and access to authorized staff inform students' risk assessments.

4.3 Readiness in Specific Academic Situations

Readiness was relatively pronounced for specific tasks described with supporting conditions. Some 247/287 students (86.1%) were ready to ask AI about straightforward academic information governed by clear rules; 247/284 (87.0%) were willing to consider course or study-pathway recommendations if they could subsequently consult an adviser. Receiving early alerts with an explanation and guidance on accessing support was endorsed by 256/286 (89.5%). These percentages must be interpreted in light of each entire statement, including its conditions.

Table 3: Readiness to Use AI in Specific Academic Situations

Assessment item	n	M ± SD	Levels 4–5, n (%)
RA1. Straightforward inquiries governed by clear rules	287	4.21 ± 0.81	247 (86.1)
RA2. Considering pathways if adviser consultation remains possible	284	4.23 ± 0.76	247 (87.0)
RA3. Alerts with explanations and support guidance	286	4.25 ± 0.74	256 (89.5)
RA4. Providing data if purpose and safeguards are clear	288	3.82 ± 0.76	208 (72.2)
RA5. Participating in pilots and providing feedback	282	4.14 ± 0.83	232 (82.3)
RA6. Use only if human contact remains available	288	3.87 ± 0.88	206 (71.5)

Note. Levels 4–5 indicate agreement or strong agreement with the whole statement, including any condition. Percentages use the valid n for each item; overall sample N = 288. RA6 expresses a condition of use and was not reverse-coded to construct an overall readiness score.

Providing necessary data when the purpose and safeguards were explained received agreement from 208/288 (72.2%). This was descriptively lower than readiness to seek information, receive recommendations, or obtain alerts, suggesting greater caution when interactions require students to provide personal information. In addition, 206/288 (71.5%) agreed that they would use AI only if they retained the option to contact a person. Because this statement imposes a stringent condition, disagreement cannot automatically be equated with rejecting AI or showing lower readiness. Supplementary questions further illuminate these conditions. Human review of recommendations materially affecting academic interests was supported by 242/282 (85.8%), while 254/285 (89.1%) wanted the right to request human reconsideration. A combined statement calling for feedback and complaint channels and periodic publication of accuracy levels was endorsed by 264/285 (92.6%); preventing unauthorized access or data leakage was endorsed by 260/286 (90.9%). These responses indicate expectations regarding service organization, not proof that the corresponding mechanisms exist or are usable.

The importance of accountable personnel also appeared in open-ended responses. SV193 specified the conditions 'Accurate, fast, and with someone accountable for the answers AI provides' (SV-M3). SV170 wished for 'someone to supervise and resolve problems promptly and satisfactorily whenever difficulties arise when using an AI service' (SV-M3). Alongside the general pattern of readiness, SV114 said, 'I am not quite ready yet,' and SV106 responded, 'Do not use AI,' when asked about conditions of use. Retaining these responses acknowledges variation within the sample rather than equating the overall trend with universal agreement.

4.4 Associations and Co-occurrence of Assessments

Table 4: Correlations between Perceived Benefits, AI Use, and Readiness

Variable pair	n	ρ	p	Holm-adjusted p
Perceived benefits and RA1	266	0.393	< 0.001	< 0.001
Perceived benefits and RA3	265	0.436	< 0.001	< 0.001
Academic AI use and perceived benefits	248	0.078	0.223	0.669

Note. ρ is Spearman's rank correlation coefficient; n is calculated for each variable pair. Holm-adjusted p-values derive from the seven exploratory comparisons in the original study.

Perceived-benefit scores were positively correlated with readiness to seek straightforward academic information (ρ = 0.393, n = 266) and with readiness to receive explained alerts (ρ = 0.436, n = 265). Both associations had Holm-adjusted p < 0.001. By contrast, academic AI-use scores showed a correlation of ρ = 0.078 with perceived benefits (n = 248; Holm-adjusted p = 0.669). The third comparison thus provides no clear statistical evidence of an association in this sample,

whereas the first two indicate that students rating benefits more highly also tended to express greater readiness in the surveyed situations.

Respondent-level co-occurrence offers additional evidence for interpreting positive attitudes and caution together. A total of 219 students selected levels 4–5 both for readiness to seek straightforward academic information and for concern about inaccurate or outdated information, equivalent to 76.0% of all 288 responses. Similarly, 223 were ready to receive explained alerts while also requiring human review of recommendations significantly affecting academic interests, representing 77.4% of the sample. These are proportions endorsing two items simultaneously, not association coefficients or evidence of a cause of readiness. Nevertheless, they show that concern about risk can coexist with the desire to use AI among many students.

5 DISCUSSION AND MANAGEMENT IMPLICATIONS

The findings indicate that perceptions of AI in academic administration are organized around tasks students need to complete and around the reliability of support processes. Positively assessed benefits primarily involve faster access to information, less waiting, and progress monitoring, whereas prominent risks concern misapplied information and inappropriate recommendations. The simultaneous presence of these assessments suggests that students attend both to potential utility and to the conditions under which it can be realized. This interpretation shifts the focus from general approval of technology to the quality of academic-service interactions students expect.

The positive correlations between perceived benefits and readiness in two situations are consistent with the explanatory relevance of perceived usefulness in technology-acceptance research [5]. However, they must be interpreted at the appropriate analytical level: this study examined bivariate associations without controlling for other respondent characteristics. Bilquise et al. [4] found no statistically significant relationship between perceived usefulness and intention to adopt an academic advising chatbot in their model. Differences in functions, question wording, and analytical procedures warrant caution in transferring findings across contexts. The present evidence adds a within-sample association, not proof that usefulness is a universal determinant.

The coexistence of expected benefits and concerns also resembles Chan and Hu [3] findings on student perspectives towards generative AI in education. The contribution of the present case is to locate these assessments within academic information, study-pathway choices, and academic alerts, where inaccurate information may alter student decisions. In particular, the fact that 76.0% of the full sample were simultaneously ready to ask simple questions and concerned about inaccurate information suggests that caution does not necessarily preclude seeking support. Yet, because agreement with the individual items was already high and the risk–readiness association was not separately tested, this co-occurrence does not establish an independent acceptance mechanism.

Importantly, many readiness items already included conditions, such as the possibility of consulting an adviser or receiving an explanation for an alert. High agreement therefore indicates readiness for the form of support described in the item. The study did not compare an identical function with and without safeguards, and thus cannot quantify any change in readiness attributable to a particular safeguard. The practical value of these findings lies in identifying support arrangements respondents assessed favourably, which may guide subsequent service design and testing.

Caution about data provision also underscores the distinction between wanting assistance and consenting to the processing of personal information. Soffer and Cohen [7] situate this issue at the intersection of educational benefits, privacy, and institutional transparency. In this sample, willingness to provide data was descriptively lower than readiness to receive information or alerts, but the evidence does not establish that the difference results from a benefits–privacy trade-off. Universities should clarify data categories, purposes, and procedures for handling requests before expecting participation in personalized services requiring personal information.

Findings on referral, reconsideration, and responsibility indicate that staff members or advisers need clearly defined roles in service delivery. When cases are not explicitly covered by regulations, access to someone who can receive the request and assess individual circumstances helps preserve students' capacity to resolve academic matters. This implication accords with Miao and Holmes [13] human-centred approach to educational AI and specifies the connections among accountability, transparency, and trust in educational data use discussed by Pardo and Siemens (2014). Institutional responsibility should therefore be operationalized through accessible points of reception, review, and correction.

A practical priority is to standardize information sources before introducing AI-based inquiries. The academic administration unit and relevant departments should verify regulations, curricula, academic calendars, forms, and applicability by admission cohort, while assigning responsibility for updates when documents change. AI responses should link to official sources and state the applicable conditions; cases lacking adequate grounds should be referred to

responsible staff. Because this proposal responds jointly to demand for timely access and concern about inaccurate or expired information, implementation should be evaluated for both accuracy and task completion.

For study-pathway advice and academic alerts, procedures should specify which functions AI may support and when human review is mandatory. Students should be able to request an explanation, provide additional information, or seek reconsideration without repeating the entire contact process. Recommendations with substantial consequences for academic interests should be referred to authorized personnel before being used as a basis for decisions. At the same time, information about data categories, access rights, and requests for data correction should be communicated in accessible language to address survey concerns.

Student guidance should use practical academic situations, such as identifying an expired notice, checking registration requirements for a particular cohort, or determining when an adviser must be contacted. It should also distinguish personal AI tools from official services and help students decide what information is appropriate to disclose. Activities could be integrated into first-year orientation and academic advising, with exercises requiring learners to identify sources and justify their proposed actions. This approach aligns awareness-building in educational digital transformation with students' concrete tasks (Prime Minister of Vietnam, 2022).

The proposed measures should be examined through clearly scoped pilots before expansion. Pilot evaluation should track information accuracy, request-resolution rates, time to staff referral, correction mechanisms, and learner experiences. Surveyed readiness can inform the choice of functions to pilot, but decisions to sustain or scale them should also be based on operational outcomes and available resources. Feedback from both willing and hesitant students may expose accessibility conditions obscured by high overall agreement.

Several limitations should be considered when using these findings. This volunteer sample came from a single major at one university and was 93.4% female; the results cannot be generalized to all students or establish distinctive characteristics of Chinese Language majors. Single-time-point self-reports may be affected by item interpretation, acquiescence, and common-method influences, while actual usage behaviours and academic task outcomes were not observed. Open-ended answers add meaning to the quantitative findings but were generally brief and cannot fully explain the formation of individual assessments. Future research could compare majors, contrast equivalent situations with and without safeguards, and combine pilot observation with surveys to examine the transition from readiness to actual use.

6 CONCLUSION

The survey of 288 Chinese Language majors at the University of Foreign Language Studies, the University of Danang, shows that anticipated benefits, risk perceptions, and readiness to use AI coexist in students' assessments of academic administration. Respondents positively evaluated faster information access, reduced waiting, and progress monitoring while expressing concern about accuracy, suitability of recommendations, and access to accountable personnel. Perceived benefits were positively correlated with readiness in two surveyed situations, and joint responses show that concerns about risk may accompany the desire to use AI. These findings support standardizing information sources, retaining human review and reconsideration, protecting data, and providing task-based academic guidance. Within the limits of available evidence, conditional readiness accurately captures the wording of survey items; application effectiveness and factors influencing actual behaviour require further investigation.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclaimer (Artificial intelligence)

Author(s) hereby declare that AI-assisted language editing tools were used only to support language polishing and revision. The authors remain fully responsible for the study design, data, analysis, interpretation, references, and final content of the manuscrip

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