Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Academic Stewardship through AI-Enabled Learning Governance: Ethical Systems for Inclusive Learner Support in Higher Education

Chi Che

chi_c@payap.ac.th

Educational Leadership Department, Payap University https://orcid.org/0009-0000-3466-994X

Brian Perkins

Columbia University Teachers College

Research Article

Keywords: AI governance, Higher education, Learner support, Academic stewardship, Inclusive education

Posted Date: May 21st, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9759894/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Abstract

Artificial intelligence is increasingly embedded in higher education through learning analytics, automated feedback, generative AI tools, academic advising, early-alert systems, and student-support chatbots. In Chinese higher education, these developments create opportunities for scalable learner support but also raise ethical concerns related to privacy, bias, transparency, accountability, learner agency, and inclusion. This study develops and examines an ethical academic stewardship framework for AI-enabled learning governance in Chinese higher education. Using a sequential explanatory mixed-methods design, survey data were collected from 628 respondents across six stakeholder groups in selected higher education institutions in Sichuan Province, followed by semi-structured interviews. Results showed high expectations for human oversight (M = 4.18, SD = 0.62), learner agency (M = 4.11, SD = 0.65), inclusive support (M = 4.09, SD = 0.66), and privacy protection (M = 4.06, SD = 0.68), while transparency perception (M = 3.21, SD = 0.76) and governance readiness (M = 3.37, SD = 0.74) were comparatively lower. Regression analysis explained 58% of the variance in governance readiness, with institutional policy clarity (β = .29), transparency (β = .24), human oversight (β = .18), and inclusive support (β = .16) emerging as key predictors. Qualitative findings further emphasized visible data rules, human review, bias control, accessibility, and appeal mechanisms. The study contributes a practical framework connecting institutional responsibility, data stewardship, algorithmic accountability, human-centered intervention, and inclusive learner outcomes.

1 Introduction

1.1 AI-enabled learner support and the governance challenge in Chinese higher education

Artificial intelligence is increasingly reshaping higher education through adaptive learning systems, learning analytics, automated feedback, intelligent tutoring, academic advising, student-support chatbots, and generative AI tools. Earlier reviews of artificial intelligence in higher education showed that AI applications were expanding across teaching, learning, assessment, prediction, recommendation, and institutional decision-making, while also noting that educational and ethical perspectives were often less developed than technical applications (Zawacki-Richter et al. 2019; Chen et al. 2020). More recent studies suggest that AI in higher education is no longer limited to isolated instructional tools; rather, it is becoming part of a wider institutional infrastructure for learning support, academic monitoring, student engagement, and educational decision-making (Crompton and Burke 2023; Ouyang et al. 2022). This shift creates a new governance problem: universities must not only decide whether to adopt AI, but also how to govern AI-enabled learner support in ways that are educationally meaningful, ethically defensible, and institutionally accountable.

AI-enabled learner support refers to the use of AI systems to assist students' learning progress, feedback, advising, academic planning, accessibility, early warning, and student services. Within higher education, such support may include adaptive platforms that personalize learning pathways, analytics

dashboards that identify academic risk, automated feedback systems that support formative assessment, generative AI tools that assist writing and inquiry, and advising technologies that recommend learning resources or support interventions. These tools can make learner support more timely, scalable, and personalized. However, they also mediate how institutions classify students, interpret learning behavior, allocate support, and communicate academic risk. As a result, AI-enabled learner support affects not only learning efficiency but also student rights, institutional responsibility, and educational fairness.

In Chinese higher education, AI-enabled learner support is developing within a broader context of digital education, smart campus construction, educational modernization, and data-informed governance. China has become an important site of AI-in-education research and implementation, and studies have increasingly examined how Chinese universities and educators perceive, adopt, and govern AI tools (Crompton and Burke 2023; Xu et al. 2024; Wang et al. 2025). Yet the rapid expansion of AI in teaching, learning, assessment, advising, and student services also raises concerns about personal information protection, data security, algorithmic bias, learner autonomy, explainability, accountability, and the appropriate role of human judgment. In this context, AI adoption alone is insufficient. Universities need governance mechanisms that clarify how AI systems are selected, implemented, monitored, explained, corrected, and aligned with inclusive learner support.

This study therefore positions AI-enabled learner support as a matter of learning governance rather than merely educational technology adoption. Learning governance refers to the institutional arrangements, policies, responsibilities, procedures, and ethical safeguards through which universities shape the use of AI in learner-facing systems. This perspective shifts the focus from whether AI can improve educational efficiency to whether universities can ensure that AI-supported decisions remain transparent, fair, accountable, and human-centered. Such a shift is especially important when AI outputs influence academic advising, feedback, early-alert interventions, support allocation, accessibility services, or student progression. In these situations, AI should function as a support mechanism for educational judgment, not as an autonomous substitute for professional responsibility.

1.2 Ethical AI, data stewardship, algorithmic accountability, and inclusion

The ethical governance of AI-enabled learner support begins with student data. AI systems in higher education often depend on learning records, platform interactions, assessment data, attendance patterns, advising histories, demographic information, and behavioral traces generated through digital learning environments. Learning analytics research has long emphasized that such data can support timely intervention and improved educational decision-making, but it also raises ethical issues related to privacy, consent, surveillance, data ownership, and institutional responsibility (Siemens 2013; Slade and Prinsloo 2013; Pardo and Siemens 2014). Student data cannot be treated as a neutral technical input because it represents learner behavior, academic history, identity, vulnerability, and educational

opportunity. For this reason, data stewardship is a foundational dimension of AI-enabled learning governance.

Data stewardship requires universities to establish clear rules for data collection, consent, access, storage, analysis, retention, deletion, and communication with students. Studies on learning analytics ethics show that students may have different expectations regarding privacy, consent, institutional data use, and the purposes for which their learning data are processed (Ifenthaler and Schumacher 2016; Rubel and Jones 2016; Li et al. 2022). These concerns are particularly important in AI-enabled learner support because predictive systems and analytics dashboards can classify students, flag academic risk, or recommend interventions based on data that students may not fully understand or control. Therefore, ethical AI governance must make data practices visible, interpretable, and contestable. Students should know when data are collected, how AI is involved, what purposes the data serve, and what options they have to question, correct, or restrict inappropriate use.

Beyond data protection, algorithmic accountability is another central requirement. AI systems can produce unequal or biased outcomes when training data, model assumptions, institutional practices, or user interpretations reflect existing inequalities. Algorithmic bias in education can disadvantage students by misclassifying learning behavior, underestimating potential, over-identifying risk, or producing recommendations that reproduce prior patterns of privilege and disadvantage (Baker and Hawn 2022). The problem is not only technical; it is also institutional and social. Bias may emerge from incomplete data, unequal access to digital tools, differences in institutional resources, language variation, disability-related needs, urban–rural disparities, or assumptions embedded in educational platforms. As a result, fairness in AI-enabled learner support requires more than model accuracy. It requires bias auditing, explainability, human review, and attention to the social contexts in which AI systems operate.

Inclusion is therefore a core governance concern. AI can potentially expand learner support by offering personalized feedback, flexible access, academic alerts, and targeted resources. However, it may also deepen inequality if learners differ in digital access, AI literacy, language background, disability status, socioeconomic resources, or institutional support capacity. Research on AI in education has repeatedly highlighted both opportunities and risks, showing that AI may enhance learning while also creating challenges related to fairness, transparency, accountability, and student trust (Hwang et al. 2020; Chiu et al. 2023; Bearman et al. 2023). In Chinese higher education, where institutions vary in mission, resources, digital infrastructure, and student populations, inclusive AI governance must consider whether AI-enabled support systems are accessible, equitable, culturally sensitive, and responsive to diverse learner needs.

Human-centered governance provides a further safeguard. Ethical AI in education should not rely only on abstract principles or technical compliance. Several studies argue that AI ethics requires operational mechanisms that connect principles to practice, including institutional accountability, human oversight, transparency, and participatory governance (Floridi et al. 2018; Jobin et al. 2019; Holmes et al. 2022;

Nguyen et al. 2023). Principles alone cannot guarantee ethical AI if institutions lack procedures for implementation, monitoring, correction, and accountability (Mittelstadt 2019). In higher education, this means that AI-supported recommendations should be reviewed by educators, advisors, counselors, or administrators when they influence meaningful learner outcomes. Students should also have agency within AI-supported processes, including the right to receive explanations, raise concerns, correct inaccurate data, and appeal decisions that affect their learning opportunities.

1.3 Research gap, study aim, and proposed academic stewardship framework

Although the literature on AI in higher education has expanded rapidly, three gaps remain. First, much existing research focuses on AI adoption, user acceptance, opportunities, challenges, or specific tools, while less attention has been given to institutional governance mechanisms for AI-enabled learner support. Studies have examined educators' and students' perceptions of AI and generative AI in higher education, including benefits, concerns, acceptance, self-efficacy, professional development needs, and trust (Chan and Hu 2023; Kasneci et al. 2023; Shahzad et al. 2024; Jo 2024; Mah and Groß 2024). However, these studies do not fully explain how universities should organize governance structures that protect privacy, fairness, transparency, learner agency, and inclusion when AI systems are embedded in learner-support services.

Second, ethical AI principles are often discussed at a broad level, but universities need operational frameworks that translate ethical principles into institutional procedures. Existing work on AI ethics, explainability, responsible AI, and learning analytics ethics provides important conceptual foundations for privacy, accountability, transparency, fairness, and human oversight (Pardo and Siemens 2014; Kitto and Knight 2019; Barredo Arrieta et al. 2020; Holmes et al. 2022; Nguyen et al. 2023). Yet higher education institutions require practical governance models that specify who is responsible, what procedures are needed, how risks are monitored, how students are informed, and how AI-supported decisions can be reviewed or challenged. Without such mechanisms, ethical AI may remain a normative aspiration rather than an institutional practice.

Third, limited empirical work has examined how stakeholders in Chinese higher education perceive ethical risks and governance expectations related to AI-enabled learner support. Recent studies on AI adoption in Chinese universities and Chinese educators' acceptance of AI tools provide valuable evidence on institutional readiness, perceived usefulness, trust, and adoption challenges (Xu et al. 2024; Wang et al. 2025). However, more research is needed on how different stakeholder groups—including students, faculty members, advisors, support staff, administrators, and IT/data personnel—understand the governance requirements of AI-supported learner services. This multi-stakeholder perspective is important because AI governance is not only a technical function managed by IT departments; it is an academic, ethical, administrative, and pedagogical responsibility distributed across the university.

To address these gaps, this study develops and examines an ethical academic stewardship framework for AI-enabled learning governance in Chinese higher education. The study is situated in Chinese higher

education, with empirical data collected from selected higher education institutions in Sichuan Province as the respondent-institution setting. Sichuan is used as a practical data-collection site because it includes diverse institutional types, including research universities, provincial public universities, applied universities, vocational colleges, and private higher education institutions. However, the conceptual contribution of the study is framed at the broader level of Chinese higher education rather than as a province-specific case.

The study is guided by the following research questions:

RQ1. How do key stakeholders in Chinese higher education perceive the use of AI-enabled systems for learner support?

RQ2. What ethical risks are most salient in AI-enabled learner support, particularly regarding privacy, bias, transparency, surveillance, accountability, and learner agency?

RQ3. What governance mechanisms are perceived as necessary to ensure ethical, inclusive, and human-centered AI-enabled learner support?

RQ4. How can an academic stewardship framework support ethical AI-enabled learning governance in Chinese higher education?

Based on the integrated literature, this study proposes academic stewardship as the core governance logic for AI-enabled learner support. Academic stewardship refers to the institutional responsibility to ensure that AI-supported educational systems protect learner dignity, data rights, fairness, agency, inclusion, and educational value. The proposed framework contains five interconnected dimensions. First, academic stewardship establishes institutional responsibility through policy, training, oversight, and accountability. Second, data stewardship governs consent, privacy, security, and data minimization. Third, algorithmic accountability addresses transparency, explainability, bias auditing, and risk review. Fourth, human-centered intervention ensures that faculty, advisors, counselors, administrators, and students remain active participants in learner-support decisions. Fifth, inclusive learner support connects AI governance to accessibility, equity, agency, well-being, and retention. The framework also includes continuous monitoring and stakeholder feedback, recognizing that responsible AI governance is iterative rather than static.

2 Methods

2.1 Research design, context, and participants

This study adopted a sequential explanatory mixed-methods design to examine ethical AI-enabled learning governance in Chinese higher education. The quantitative phase used a cross-sectional survey to identify stakeholder perceptions of AI-enabled learner support, ethical-risk awareness, and governance expectations. The qualitative phase used semi-structured interviews to explain the

quantitative patterns in greater depth and to refine the proposed academic stewardship framework. This design was appropriate because the study aimed not only to measure perceptions across respondent groups but also to interpret why particular governance concerns, such as privacy, transparency, human oversight, and inclusion, were considered important.

The study was situated in Chinese higher education, with empirical data collected from selected higher education institutions in Sichuan Province. Sichuan was used as the respondent-institution setting because it contains diverse institutional types, including research-intensive universities, provincial public universities, applied universities, vocational colleges, and private higher education institutions. The study did not treat Sichuan as a province-specific policy case; rather, it used the institutional diversity of Sichuan as a practical sampling context for examining broader issues of AI-enabled learning governance in Chinese higher education. This design allowed the study to include stakeholders from different institutional environments while keeping the conceptual contribution focused on Chinese higher education as a whole.

A multi-stage stratified purposive sampling strategy was used. In the first stage, higher education institutions were selected to represent different institutional types and geographical locations, including both Chengdu and non-Chengdu areas. In the second stage, respondents were recruited from six stakeholder groups: students, faculty members, academic advisors or counselors, student-support and inclusion staff, educational administrators, and IT/data/EdTech personnel. In the third stage, interview participants were selected from survey respondents who indicated willingness to participate in follow-up interviews, with attention to variation in respondent role, AI-use frequency, privacy concern, perceived transparency, and governance readiness.

The final survey sample consisted of 628 valid respondents. Students formed the largest group, followed by faculty members, academic advisors or counselors, student-support and inclusion staff, educational administrators, and IT/data/EdTech personnel. This distribution reflected the learner-centered focus of the study while still including institutional actors responsible for teaching, advising, support services, administration, digital platforms, and data governance. For the qualitative phase, a purposive subsample of 42 interview participants was selected, including students, faculty members, advisors, support staff, administrators, and IT/data personnel. The interviews were intended to deepen the interpretation of the survey findings and identify concrete governance mechanisms for responsible AI-enabled learner support.

Participation was limited to adults aged 18 or above who were currently studying or working in a selected Chinese higher education institution. Student participants were required to have experience with or awareness of AI tools used for learning, feedback, academic planning, advising, or student support. Faculty, staff, and administrator participants were required to have teaching, advising, support-service, administrative, digital education, or data-related responsibilities. Respondents who did not provide informed consent, submitted incomplete responses, or did not meet the role-based inclusion criteria were excluded from the final dataset.

2.2 Instruments, data collection, and data analysis

The survey instrument was developed from the integrated literature on AI in higher education, ethical AI, learning analytics, algorithmic accountability, human-centered AI, and inclusive learner support. The questionnaire contained two main parts. The first part collected demographic and institutional information, including respondent role, institution type, institutional location, AI-use frequency, and main AI-use purpose. The second part measured nine constructs related to AI-enabled learning governance: AI use experience, perceived usefulness, privacy concern, transparency perception, fairness and bias concern, human oversight expectation, learner agency, inclusive support expectation, and governance readiness. Items were measured using a five-point Likert scale, ranging from 1 = strongly disagree or very low to 5 = strongly agree or very high. The survey instrument was developed from the integrated literature on AI in higher education, learning analytics ethics, algorithmic accountability, and inclusive learner support. The full survey construct matrix and sample items are provided in Supplementary Appendix A.

The interview protocol was designed to extend and explain the survey results. Interview questions focused on current uses of AI in learning or learner support, perceived benefits and risks, privacy and student-data concerns, fairness and bias concerns, transparency and explainability expectations, human oversight, learner agency, appeal mechanisms, institutional policy readiness, and inclusion-related challenges. Interviewees were encouraged to provide examples from teaching, learning, advising, student services, platform management, or administrative practice. This approach allowed the qualitative phase to capture both stakeholder perceptions and practical governance expectations. The semi-structured interview protocol was designed to explore participants' perceptions of AI-enabled learner support, ethical risks, governance expectations, and inclusion-related concerns. The interview protocol is provided in Supplementary Appendix B.

Survey data were collected online. Before completing the questionnaire, participants received an information statement explaining the study purpose, voluntary participation, confidentiality, and the right to withdraw. After invalid and incomplete responses were removed, 628 valid responses were retained for analysis. Semi-structured interviews were conducted after the preliminary survey analysis so that interview selection and questioning could be informed by emerging quantitative patterns. Interviews were recorded with participant consent, transcribed, checked for accuracy, and anonymized before analysis.

Quantitative data were analyzed using descriptive statistics, reliability analysis, group comparison, and multiple regression. Descriptive statistics were used to summarize respondent characteristics, AI-use patterns, and mean scores for the main governance constructs. Cronbach's alpha was calculated to assess the internal consistency of each construct. One-way analysis of variance was used to examine whether perceptions differed across respondent groups. Multiple regression analysis was then conducted to identify predictors of governance readiness, with privacy protection, transparency, fairness

and bias control, human oversight, learner agency, inclusive support, and institutional policy clarity entered as predictors.

Qualitative data were analyzed using thematic analysis. The initial coding scheme was informed by the proposed academic stewardship framework, including data stewardship, algorithmic accountability, human-centered intervention, learner agency, inclusive support, and institutional responsibility. Additional inductive codes were added when interviewees raised new or context-specific concerns. Themes were compared across stakeholder groups to identify convergent and divergent perspectives. Finally, the quantitative and qualitative findings were integrated to refine the proposed framework. The integration focused on explaining why certain constructs were highly rated, why governance readiness appeared comparatively lower, and how universities could translate ethical AI principles into practical governance mechanisms for learner support.

3 Results

3.1 Respondent profile and AI-use characteristics

A total of 628 valid responses were retained for analysis. As shown in Table 1, students constituted the largest respondent group (n = 410, 65.3%), followed by faculty members (n = 96, 15.3%), academic advisors or counselors (n = 38, 6.1%), educational administrators (n = 34, 5.4%), student-support or inclusion staff (n = 26, 4.1%), and IT/data/EdTech staff (n = 24, 3.8%). The sample covered different institutional types, including research-intensive universities, provincial public universities, applied universities, vocational colleges, and private higher education institutions. Slightly more than half of the respondents were from institutions located in Chengdu (54.5%), while 45.5% were from non-Chengdu areas.

The data also indicate that AI use was already visible among respondents. More than half of the participants reported using AI tools either often (39.2%) or very often (17.4%), while 28.5% reported using them sometimes. Only 3.7% reported never using AI tools. The most common AI-use purpose was learning support (45.9%), followed by teaching and feedback (14.0%), student services or administration (12.4%), academic advising (9.9%), data analysis or platform management (9.2%), and assessment or academic integrity (8.6%). These results suggest that AI-enabled tools were not limited to teaching and learning but were also being used across advising, assessment, administration, and data-related functions.

Table 1
Respondent profile and AI-use characteristics

Variable	Category	n	%
Respondent role	Students	410	65.3
	Faculty members	96	15.3
	Academic advisors/counselors	38	6.1
	Student-support/inclusion staff	26	4.1
	Educational administrators	34	5.4
	IT/data/EdTech staff	24	3.8
Institution type	Research-intensive university	126	20.1
	Provincial public university	158	25.2
	Applied university	132	21.0
	Vocational college	116	18.5
	Private higher education institution	96	15.3
Institutional location	Chengdu	342	54.5
	Non-Chengdu areas	286	45.5
AI-use frequency	Never	23	3.7
	Rarely	71	11.3
	Sometimes	179	28.5
	Often	246	39.2
	Very often	109	17.4
Main AI-use purpose	Learning support	288	45.9
	Teaching and feedback	88	14.0
	Academic advising	62	9.9
	Assessment and academic integrity	54	8.6
	Student services/administration	78	12.4
	Data analysis/platform management	58	9.2

3.2 Descriptive patterns of ethical AI governance constructs

Table 2 presents the descriptive statistics, reliability coefficients, and respondent-group differences for the nine AI-enabled learning governance constructs. All constructs showed acceptable to excellent internal consistency, with Cronbach's alpha values ranging from .79 to .91. This indicates that the measurement scales were sufficiently reliable for further analysis.

The highest mean score was found for human oversight expectation (M = 4.18, SD = 0.62), followed by learner agency (M = 4.11, SD = 0.65), inclusive support expectation (M = 4.09, SD = 0.66), and privacy concern (M = 4.06, SD = 0.68). These results suggest that respondents strongly expected AI-enabled learner support to remain human-reviewed, learner-sensitive, inclusive, and privacy-protective. Respondents also reported relatively high concern about fairness and bias (M = 3.94, SD = 0.73) and perceived usefulness (M = 3.82, SD = 0.71).

By contrast, transparency perception (M = 3.21, SD = 0.76) and governance readiness (M = 3.37, SD = 0.74) received comparatively lower mean scores. This pattern suggests a gap between the perceived importance of ethical AI governance and the perceived maturity of current institutional arrangements. In other words, respondents recognized the value of AI-enabled learner support but were less confident that institutions had already developed sufficiently transparent and systematic governance mechanisms.

Group differences were statistically significant for all constructs. IT/data/EdTech staff reported the highest level of AI use experience and governance readiness, which may reflect their greater familiarity with digital systems and platform management. Students reported the highest privacy concern and learner agency expectations, indicating stronger sensitivity to how AI systems collect data, make recommendations, and affect student autonomy. Faculty members reported the highest expectation for human oversight, suggesting that teachers remained concerned about preserving professional judgment in AI-supported educational decisions. Student-support and inclusion staff reported the highest fairness and bias concern and inclusive support expectation, which is consistent with their institutional role in supporting diverse and potentially vulnerable learner groups.

Table 2
Descriptive statistics, reliability, and group differences for AI-enabled learning governance constructs

Construct	Items	Cronbach's α	Mean	SD	Highest-Rated Group	Group Difference
AI use experience	4	.82	3.56	0.88	IT/data/EdTech staff	$F(5, 622) = 8.42$, $p < .001$, $\eta^2 = .064$
Perceived usefulness	5	.88	3.82	0.71	Students	$F(5, 622) = 4.76$, $p < .001$, $\eta^2 = .037$
Privacy concern	5	.86	4.06	0.68	Students	$F(5, 622) = 5.31$, $p < .001$, $\eta^2 = .041$
Transparency perception	4	.79	3.21	0.76	Educational administrators	$F(5, 622) = 6.18$, $p < .001$, $\eta^2 = .047$
Fairness and bias concern	5	.90	3.94	0.73	Student-support/inclusion staff	$F(5, 622) = 7.26$, $p < .001$, $\eta^2 = .055$
Human oversight expectation	4	.84	4.18	0.62	Faculty members	$F(5, 622) = 3.92$, $p = .002$, $\eta^2 = .031$
Learner agency	4	.87	4.11	0.65	Students	$F(5, 622) = 4.44$, $p = .001$, $\eta^2 = .034$
Inclusive support expectation	5	.91	4.09	0.66	Student-support/inclusion staff	$F(5, 622) = 6.87$, $p < .001$, $\eta^2 = .052$
Governance readiness	5	.89	3.37	0.74	IT/data/EdTech staff	$F(5, 622) = 5.74$, $p < .001$, $\eta^2 = .044$

Figure 2 visually confirms the pattern shown in Table 2. Across respondent groups, mean scores were relatively high for privacy concern, human oversight expectation, learner agency, and inclusive support expectation. However, transparency perception and governance readiness were lower across most groups. This contrast indicates that stakeholders expected AI-enabled learner support to be ethically governed but did not perceive current institutional governance capacity as equally developed.

The figure also illustrates role-based differences. Students reported higher concern for privacy and learner agency, while faculty members emphasized human oversight. Support and inclusion staff placed stronger emphasis on fairness, bias control, and inclusive support. Administrators and IT/data staff reported relatively higher governance readiness, although their scores still remained moderate rather than high. This pattern suggests that AI governance is perceived differently depending on stakeholders'

relationship to AI-enabled learner support: students are most concerned with rights and autonomy, faculty with professional judgment, support staff with equity, and technical or administrative staff with institutional readiness.

3.3 Predictors of governance readiness

Multiple regression analysis was conducted to identify predictors of perceived governance readiness for AI-enabled learner support. As shown in Table 3, the model was statistically significant and explained 58% of the variance in governance readiness, $R^2 = .58$, adjusted $R^2 = .57$, $F(7, 620) = 122.37$, $p < .001$. This indicates that the selected ethical governance variables collectively provided strong explanatory power.

Among the predictors, institutional policy clarity was the strongest predictor of governance readiness ($\beta = .29$, $p < .001$). This suggests that respondents were more likely to perceive institutions as ready for AI-enabled learning governance when clear policies, responsibilities, procedures, and rules were in place. Transparency was the second strongest predictor ($\beta = .24$, $p < .001$), indicating that visible and understandable AI procedures were central to stakeholder confidence. Human oversight also significantly predicted governance readiness ($\beta = .18$, $p < .001$), showing that respondents associated responsible AI implementation with human review and professional judgment.

Inclusive support was another significant predictor ($\beta = .16$, $p < .001$), suggesting that AI governance was perceived as stronger when systems were expected to support diverse learners fairly and accessibly. Fairness and bias control also made a significant contribution ($\beta = .13$, $p = .003$), confirming that respondents viewed bias monitoring as an important governance mechanism. Learner agency ($\beta = .11$, $p = .001$) and privacy protection ($\beta = .10$, $p = .013$) were also significant, though their effects were more modest. Overall, the regression results indicate that governance readiness depends not only on technical capacity but also on policy clarity, transparency, human oversight, inclusion, fairness, student agency, and privacy protection.

Table 3
Predictors of governance readiness for AI-enabled learner support

Predictor	B	SE	β	t	p	Interpretation
Privacy protection	0.10	0.04	.10	2.50	.013	Stronger privacy protection modestly predicts higher governance readiness.
Transparency	0.22	0.03	.24	7.33	< .001	Transparency is a strong predictor of perceived governance readiness.
Fairness and bias control	0.12	0.04	.13	3.00	.003	Bias-control mechanisms significantly strengthen governance readiness.
Human oversight	0.17	0.04	.18	4.25	< .001	Human review is an important condition for responsible AI governance.
Learner agency	0.10	0.03	.11	3.33	.001	Appeal, correction, and student voice contribute to governance readiness.
Inclusive support	0.15	0.04	.16	3.75	< .001	Inclusive support expectations significantly predict governance readiness.
Institutional policy clarity	0.28	0.03	.29	9.33	< .001	Policy clarity is the strongest predictor of governance readiness.

3.4 Qualitative themes explaining governance expectations

The qualitative interview findings helped explain why respondents gave high scores to privacy, human oversight, learner agency, and inclusive support, while rating transparency and governance readiness more moderately. Six major themes were identified.

First, respondents emphasized that data rules must be visible to students and staff. Students in particular wanted to know what types of learning data were collected, how long the data would be stored, who could access them, and whether AI-generated recommendations would affect academic advising or support allocation. Faculty and administrators also noted that unclear data-use policies could reduce trust in AI-supported learner services. This theme supports the importance of data stewardship as a core dimension of AI-enabled learning governance.

Second, respondents repeatedly stated that human review remains essential in high-stakes learner-support decisions. Faculty members and advisors were especially concerned that AI-generated risk labels or recommendations could be misinterpreted if they were not reviewed by educators or support professionals. Interviewees generally accepted AI as a useful support tool, but they rejected the idea that AI should independently make decisions about academic risk, intervention priority, or learner potential. This theme explains why human oversight received the highest mean score among the quantitative constructs.

Third, participants viewed bias as both a technical and institutional concern. Support staff and inclusion-related respondents argued that AI systems could disadvantage students if they failed to consider disability, rural–urban differences, digital access, language background, or uneven academic preparation. IT/data staff tended to describe bias in terms of data quality and model design, while student-support staff linked bias to broader institutional inequalities. This theme suggests that bias control should not be treated as a purely technical audit but as part of inclusive academic governance.

Fourth, respondents described transparency as a foundation for trust. Several interviewees suggested that students and staff would be more willing to use AI-enabled learner support if institutions clearly explained when AI was being used, what kinds of recommendations it generated, and how decisions were reviewed. The moderate score for transparency perception in the survey indicates that current practices may not yet meet stakeholder expectations. This finding supports the regression result showing that transparency was one of the strongest predictors of governance readiness.

Fifth, participants argued that inclusion requires accessibility and contextual sensitivity. Interviewees noted that AI-enabled learner support should not only benefit students who already have strong digital access and AI literacy. Instead, institutions should ensure that AI tools are accessible to students with disabilities, students from less-resourced backgrounds, students in vocational or applied programs, and students with different levels of digital readiness. This theme explains why inclusive support expectation was rated highly and why inclusive support significantly predicted governance readiness.

Sixth, respondents emphasized that appeal mechanisms protect learner agency. Students wanted the ability to question AI-supported recommendations, correct inaccurate data, and seek human explanation when AI outputs affected their learning support. Faculty and advisors similarly emphasized that students should not be reduced to algorithmic profiles. This theme supports the inclusion of learner agency, student voice, correction procedures, and appeal channels in the refined framework.

3.5 Empirical refinement of the academic stewardship framework

The final stage of analysis integrated the quantitative and qualitative findings to refine the proposed academic stewardship framework. The results indicated that AI-enabled learning governance should begin with institutional AI governance readiness, especially policy clarity, staff training, review structures, and accountability. This refinement was supported by the regression analysis, where institutional policy clarity was the strongest predictor of governance readiness.

The second layer of the refined framework consists of ethical governance mechanisms, including data stewardship, transparency, bias auditing, human oversight, appeal channels, and learner agency. These mechanisms were supported by both the survey and interview findings. Transparency, human oversight, inclusive support, fairness and bias control, learner agency, and privacy protection all significantly predicted governance readiness. Qualitative findings further showed that respondents expected AI governance to be visible, reviewable, and open to correction.

The third layer concerns learner-support implementation, including academic advising, feedback, early alert, accessibility, and personalized support. This layer reflects the practical contexts in which AI systems are likely to affect students. The final layer concerns inclusive learner outcomes, including trust, agency, equity, well-being, retention, and responsible AI use. The framework also includes stakeholder feedback and continuous monitoring, reflecting the finding that AI governance should be iterative rather than static.

Figure 3 presents the empirically refined framework. Compared with the proposal-stage framework, the refined model places institutional AI governance readiness at the top because policy clarity emerged as the strongest predictor of governance readiness. It also gives greater prominence to transparency, human oversight, appeal channels, and inclusive support because these dimensions were strongly supported across both quantitative and qualitative findings. Overall, the refined framework suggests that responsible AI-enabled learner support in Chinese higher education requires more than digital adoption. It requires a structured governance system that connects policy clarity, ethical safeguards, human-centered review, learner agency, and inclusive educational outcomes.

4 Discussion

4.1 From AI adoption to ethical academic stewardship

The findings suggest that AI-enabled learner support in Chinese higher education should be understood not simply as a matter of technology adoption, but as a matter of institutional governance. Respondents reported relatively frequent AI use and generally positive perceptions of AI's usefulness, indicating that AI tools have already entered learning, teaching, advising, administration, and platform-management practices. This pattern is consistent with prior studies showing that AI in higher education has expanded from isolated instructional applications to broader institutional uses involving feedback, learning analytics, intelligent tutoring, student support, and academic decision-making (Zawacki-Richter et al. 2019; Crompton and Burke 2023; Ouyang et al. 2022). However, the results also show that adoption does not automatically produce trust, transparency, or governance readiness. Although respondents recognized the value of AI-enabled learner support, they rated institutional transparency and governance readiness lower than ethical expectations such as privacy protection, human oversight, learner agency, and inclusive support.

This gap between AI use and AI governance is one of the central findings of the study. Respondents did not reject AI-enabled learner support; rather, they expected it to be governed through clear policies, visible procedures, and human-centered safeguards. The regression results strengthen this interpretation. Institutional policy clarity was the strongest predictor of governance readiness, followed by transparency, human oversight, and inclusive support. This indicates that stakeholders evaluate institutional readiness not primarily by the availability of AI tools, but by whether universities have clear rules, explainable processes, review mechanisms, and learner-protection structures. In this sense, the

study supports Mittelstadt's (2019) argument that ethical principles alone cannot guarantee ethical AI. Principles must be translated into institutional arrangements, responsibilities, and procedures.

The strong role of policy clarity also supports the proposed concept of academic stewardship. Academic stewardship refers to the university's responsibility to protect learner dignity, data rights, educational fairness, agency, and inclusion while using AI to enhance learner support. This concept extends existing ethical AI frameworks by locating responsibility not only in technical design but also in academic governance, institutional policy, and professional judgment. Prior research has emphasized fairness, transparency, privacy, accountability, and human-centered AI as essential principles in education (Holmes et al. 2022; Nguyen et al. 2023; Jobin et al. 2019; Floridi et al. 2018). The present findings add that, in higher education settings, these principles require academic stewardship mechanisms: policy clarity, data stewardship, algorithmic accountability, human review, student voice, and continuous monitoring.

The high mean score for human oversight expectation is especially important. Respondents appeared willing to accept AI as a support mechanism but not as an autonomous decision-maker. Faculty members rated human oversight particularly highly, suggesting concern that AI-supported feedback, early alerts, risk classification, or advising recommendations should remain subject to professional educational judgment. This finding aligns with the wider literature arguing that AI in education should augment rather than replace human decision-making (Hwang et al. 2020; Bearman et al. 2023). In learner-support contexts, this distinction is ethically significant because AI-generated recommendations may influence academic progression, support allocation, advising pathways, or perceptions of student ability. Human oversight therefore functions as a safeguard against over-automation and protects the educational relationship between learners and institutions.

The findings also show that learner agency is a central dimension of responsible AI governance. Students rated learner agency highly, indicating that they want the ability to understand, question, correct, or appeal AI-supported decisions. This concern is closely related to learning analytics ethics, where scholars have argued that students should not be passive data subjects but should retain rights regarding how their learning data are collected, interpreted, and used (Slade and Prinsloo 2013; Pardo and Siemens 2014; Li et al. 2022). In the present study, learner agency was not only an ethical preference but also a significant predictor of governance readiness. This suggests that universities seeking to build trust in AI-enabled learner support should provide mechanisms for explanation, correction, appeal, and student participation.

4.2 Governance implications for inclusive AI-enabled learner support in Chinese higher education

The findings have direct implications for Chinese higher education institutions seeking to govern AI-enabled learner support responsibly. First, universities should establish explicit institutional policies for AI-supported learner services. These policies should clarify what AI tools are used, what data are collected, who has access to learner data, how AI-generated recommendations are reviewed, and what

responsibilities belong to faculty, advisors, administrators, IT/data staff, and student-support units. Since policy clarity was the strongest predictor of governance readiness, institutional AI policies should not remain abstract statements of principle. They should specify practical procedures for consent, data minimization, security, transparency, risk review, bias monitoring, human oversight, and appeal mechanisms.

Second, the results indicate that data stewardship should be treated as a foundational component of AI learning governance. Privacy concern was high across respondent groups, especially among students. This finding is consistent with research on learning analytics, which has long emphasized that educational data use creates ethical dilemmas around privacy, consent, surveillance, and institutional responsibility (Siemens 2013; Slade and Prinsloo 2013; Pardo and Siemens 2014). In AI-enabled learner support, data stewardship should include clear notification of data use, informed consent procedures, limits on secondary data use, secure storage, restricted access, retention rules, and procedures for correcting inaccurate learner data. Universities should avoid treating learner data as a purely technical resource because such data may affect students' academic identity, support opportunities, and institutional treatment.

Third, universities need systematic mechanisms for algorithmic accountability. Fairness and bias concern was high, and fairness and bias control significantly predicted governance readiness. This supports Baker and Hawn's (2022) argument that algorithmic bias in education can reproduce or amplify inequality if systems misclassify learners, reflect biased data, or produce unequal recommendations. In the Chinese higher education context, algorithmic accountability should include regular bias audits, model-performance review across student groups, explainability requirements, and procedures for investigating harmful or inaccurate AI outputs. Bias should not be treated only as a technical issue. It should also be understood as an institutional issue because unequal digital access, institutional resource differences, disability-related needs, language variation, and socioeconomic inequality may all affect how AI systems interpret learner data.

Fourth, inclusive learner support must become a central criterion for evaluating AI-enabled systems. Support and inclusion staff rated fairness, bias concern, and inclusive support expectation particularly highly, showing that stakeholders closest to student vulnerability are most sensitive to the equity risks of AI. This finding suggests that universities should evaluate AI tools not only by efficiency or predictive accuracy but also by whether they improve access, accessibility, student agency, and educational fairness. AI systems should be tested for usability among diverse learners, including students with disabilities, students from less-resourced backgrounds, vocational and applied-program students, and students with varying levels of digital literacy. This implication aligns with broader AI-in-education research, which emphasizes that AI creates both opportunities for personalization and risks of exclusion (Chiu et al. 2023; Holmes et al. 2022; Nguyen et al. 2023).

Fifth, transparency should be strengthened as a practical trust-building mechanism. Transparency was one of the strongest predictors of governance readiness, while transparency perception received one of

the lowest mean scores. This indicates that stakeholders want clearer explanations of when AI is used, how recommendations are generated, and how AI-supported decisions are reviewed. Explainable AI research has emphasized that transparency and interpretability are essential for responsible AI, especially when algorithmic outputs affect human decisions (Barredo Arrieta et al. 2020). In higher education, transparency should be communicated in accessible language for students, faculty, and staff. Institutions should explain the purpose of AI-supported learner services, the limits of AI-generated outputs, and the human review procedures attached to them.

Overall, the study contributes to educational technology research by proposing an academic stewardship framework that connects AI governance with learner support, institutional responsibility, and inclusion. Whereas much AI-in-education research focuses on applications, adoption, or user perceptions, this study emphasizes the governance conditions under which AI-enabled learner support can become educationally responsible. The refined framework suggests that responsible AI implementation in Chinese higher education requires a layered system: institutional policy clarity at the top, ethical governance mechanisms in the middle, learner-support implementation in practice, and inclusive learner outcomes as the ultimate purpose. This framework advances the discussion from “using AI in higher education” to “governing AI for learner support,” which is increasingly necessary as AI becomes embedded in academic advising, feedback, assessment, student services, and learning analytics systems.

5 Conclusion

This study examined AI-enabled learner support as an emerging governance challenge in Chinese higher education and proposed an ethical academic stewardship framework for guiding responsible implementation. Drawing on survey and interview findings from multiple stakeholder groups, the study identified a clear gap between the growing use of AI tools and the perceived maturity of institutional governance mechanisms. Respondents recognized the usefulness of AI for learning, feedback, advising, administration, and support services, but they also emphasized the need for stronger privacy protection, transparency, fairness and bias control, human oversight, learner agency, and inclusive support. The regression findings indicated that institutional policy clarity, transparency, human oversight, and inclusive support were the strongest contributors to perceived governance readiness, suggesting that responsible AI implementation depends less on technical adoption alone and more on visible institutional rules, review structures, and learner-protection mechanisms. The proposed academic stewardship framework contributes to educational technology research by translating ethical AI principles into a practical governance model that connects institutional responsibility, data stewardship, algorithmic accountability, human-centered intervention, and inclusive learner outcomes. For Chinese higher education institutions, the findings suggest that AI-enabled learner support should be governed as a continuous academic responsibility rather than a one-time technological innovation, with universities ensuring that AI-supported systems remain transparent, accountable, equitable, explainable, and responsive to diverse learner needs.

References

1. An, Y., Yu, J. H., & James, S. (2025). Investigating the higher education institutions' guidelines and policies regarding the use of generative AI in teaching, learning, research, and administration. *International Journal of Educational Technology in Higher Education, 22*, Article 10. https://doi.org/10.1186/s41239-025-00507-3
2. Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education, 32*, 1052–1092. https://doi.org/10.1007/s40593-021-00285-9
3. Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012
4. Bearman, M., Ryan, J., & Ajjawi, R. (2023). Discourses of artificial intelligence in higher education: A critical literature review. *Higher Education, 86*, 369–385. https://doi.org/10.1007/s10734-022-00937-2
5. Cerratto Pargman, T., & McGrath, C. (2021). Mapping the ethics of learning analytics in higher education: A systematic literature review of empirical research. *Journal of Learning Analytics, 8*(2), 123–139. https://doi.org/10.18608/jla.2021.1
6. Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education, 20*, Article 43. https://doi.org/10.1186/s41239-023-00411-8
7. Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510
8. Che, C. (2026). AI literacy as a meta-skill: A four-domain model for academic management innovation in higher education. *Frontiers in Education, 11*, Article 1755238. https://doi.org/10.3389/feduc.2026.1755238
9. Chiu, T. K. F., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 4*, Article 100118. https://doi.org/10.1016/j.caeai.2022.100118
10. Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*, Article 22. https://doi.org/10.1186/s41239-023-00392-8
11. Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., et al. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines, 28*, 689–707. https://doi.org/10.1007/s11023-018-9482-5

12. Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Buckingham Shum, S., Santos, O. C., Rodrigo, M. T., Cukurova, M., Bittencourt, I. I., & Koedinger, K. R. (2022). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education, 32*, 504–526. https://doi.org/10.1007/s40593-021-00239-1
13. Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 1*, Article 100001. https://doi.org/10.1016/j.caeai.2020.100001
14. Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development, 64*, 923–938. https://doi.org/10.1007/s11423-016-9477-y
15. Jin, Y., Yan, L., Echeverria, V., Gašević, D., & Martinez-Maldonado, R. (2025). Generative AI in higher education: A global perspective of institutional adoption policies and guidelines. *Computers and Education: Artificial Intelligence, 8*, Article 100348. https://doi.org/10.1016/j.caeai.2024.100348
16. Jo, H. (2024). From concerns to benefits: A comprehensive study of ChatGPT usage in education. *International Journal of Educational Technology in Higher Education, 21*, Article 35. https://doi.org/10.1186/s41239-024-00471-4
17. Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence, 1*, 389–399. https://doi.org/10.1038/s42256-019-0088-2
18. Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., et al. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274
19. Kitto, K., & Knight, S. (2019). Practical ethics for building learning analytics. *British Journal of Educational Technology, 50*(6), 2855–2870. https://doi.org/10.1111/bjet.12868
20. Li, W., Sun, K., Schaub, F., & Brooks, C. (2022). Disparities in students' propensity to consent to learning analytics. *International Journal of Artificial Intelligence in Education, 32*, 564–608. https://doi.org/10.1007/s40593-021-00254-2
21. Mah, D. K., & Groß, N. (2024). Artificial intelligence in higher education: Exploring faculty use, self-efficacy, distinct profiles, and professional development needs. *International Journal of Educational Technology in Higher Education, 21*, Article 58. https://doi.org/10.1186/s41239-024-00490-1
22. McDonald, N., Johri, A., Ali, A., & Collier, A. H. (2025). Generative artificial intelligence in higher education: Evidence from an analysis of institutional policies and guidelines. *Computers in Human Behavior: Artificial Humans, 3*, Article 100121. https://doi.org/10.1016/j.chbah.2025.100121
23. Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence, 1*, 501–507. https://doi.org/10.1038/s42256-019-0114-4
24. Nguyen, A., Ngo, H. N., Hong, Y., Dang, B., & Nguyen, B. P. T. (2023). Ethical principles for artificial intelligence in education. *Education and Information Technologies, 28*, 4221–4241. https://doi.org/10.1007/s10639-022-11316-w

25. Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence, 2*, Article 100020. https://doi.org/10.1016/j.caeai.2021.100020
26. Ouyang, F., Zheng, L., & Jiao, P. (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies, 27*, 7893–7925. https://doi.org/10.1007/s10639-022-10925-9
27. Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology, 45*(3), 438–450. https://doi.org/10.1111/bjet.12152
28. Rubel, A., & Jones, K. M. L. (2016). Student privacy in learning analytics: An information ethics perspective. *The Information Society, 32*(2), 143–159. https://doi.org/10.1080/01972243.2016.1130502
29. Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education, 21*, Article 46. https://doi.org/10.1186/s41239-024-00478-x
30. Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist, 57*(10), 1380–1400. https://doi.org/10.1177/0002764213498851
31. Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1509–1528. https://doi.org/10.1177/0002764213479366
32. Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments, 10*, Article 15. https://doi.org/10.1186/s40561-023-00237-x
33. Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior, 89*, 98–110. https://doi.org/10.1016/j.chb.2018.07.027
34. Wang, X., Zhao, S., Xu, X., Zhang, H., & Lei, V. N. L. (2025). AI adoption in Chinese universities: Insights, challenges, and opportunities from academic leaders. *Acta Psychologica, 258*, Article 105160. https://doi.org/10.1016/j.actpsy.2025.105160
35. Xu, S., Chen, P., & Zhang, G. (2024). Exploring Chinese university educators' acceptance and intention to use AI tools: An application of the UTAUT2 model. *SAGE Open, 14*(4). https://doi.org/10.1177/21582440241290013
36. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education, 16*, Article 39. https://doi.org/10.1186/s41239-019-0171-0

Figures

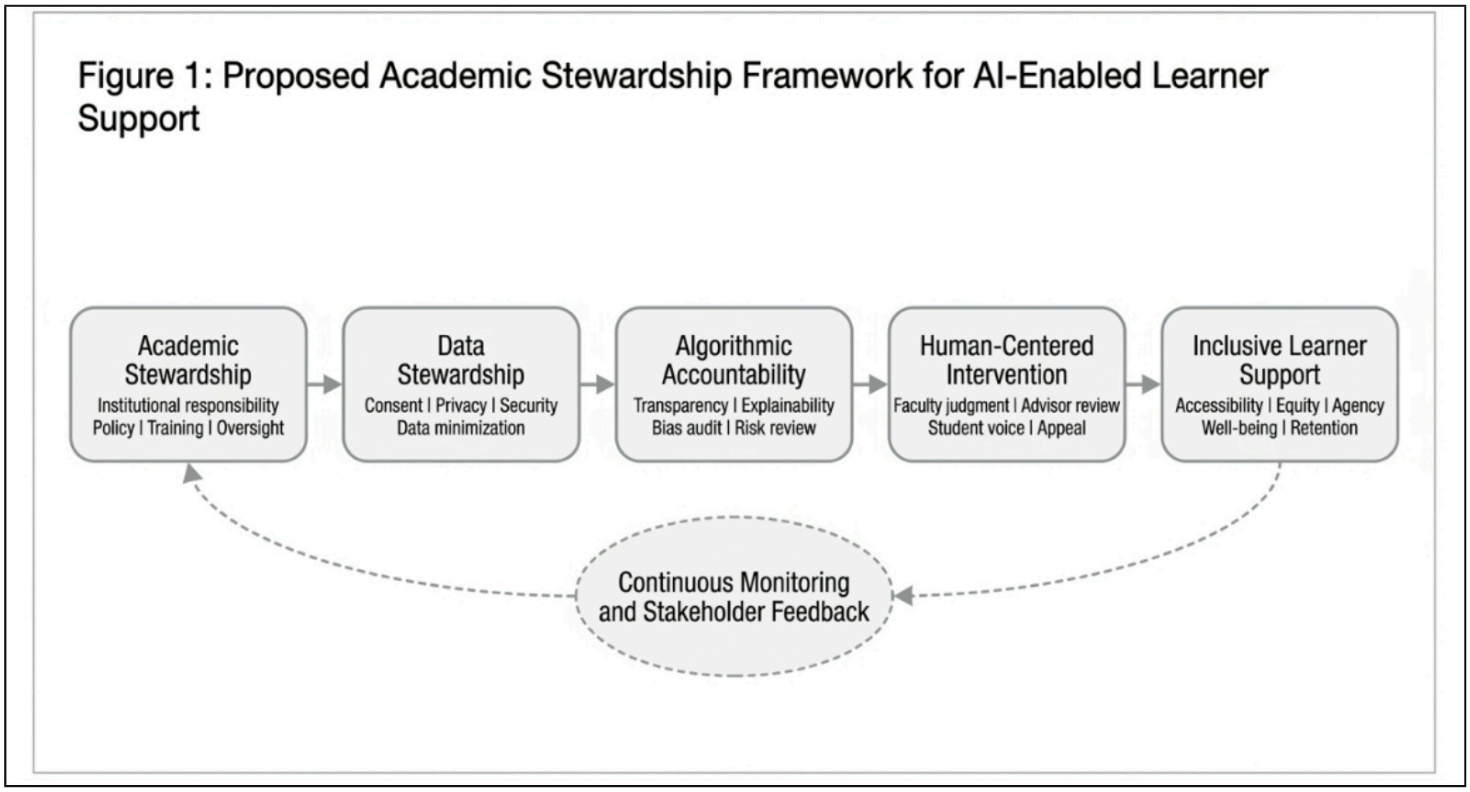


Figure 1

Proposed academic stewardship framework for AI-enabled learner support in Chinese higher education

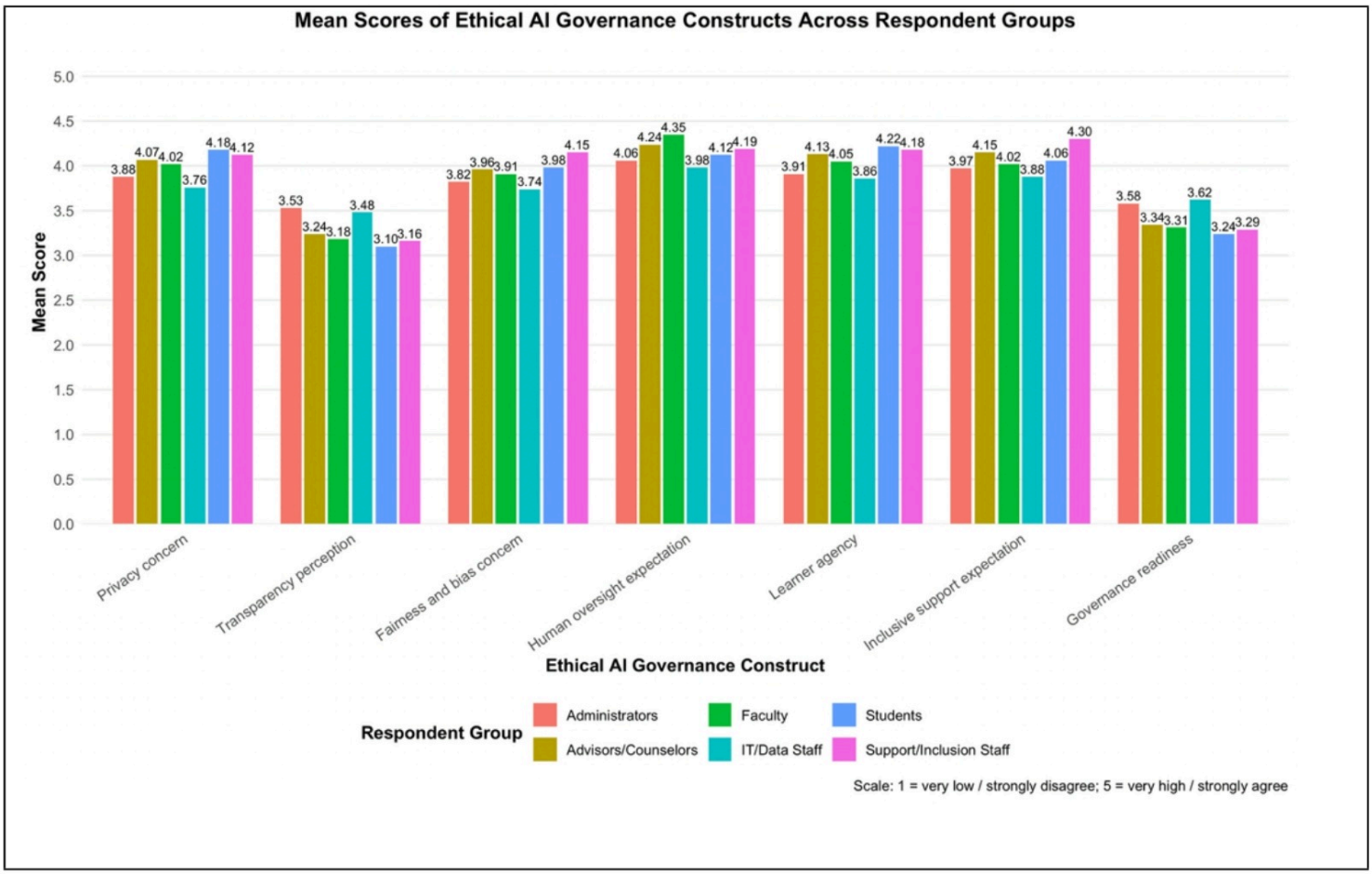


Figure 2

Mean scores of ethical AI governance constructs across respondent groups

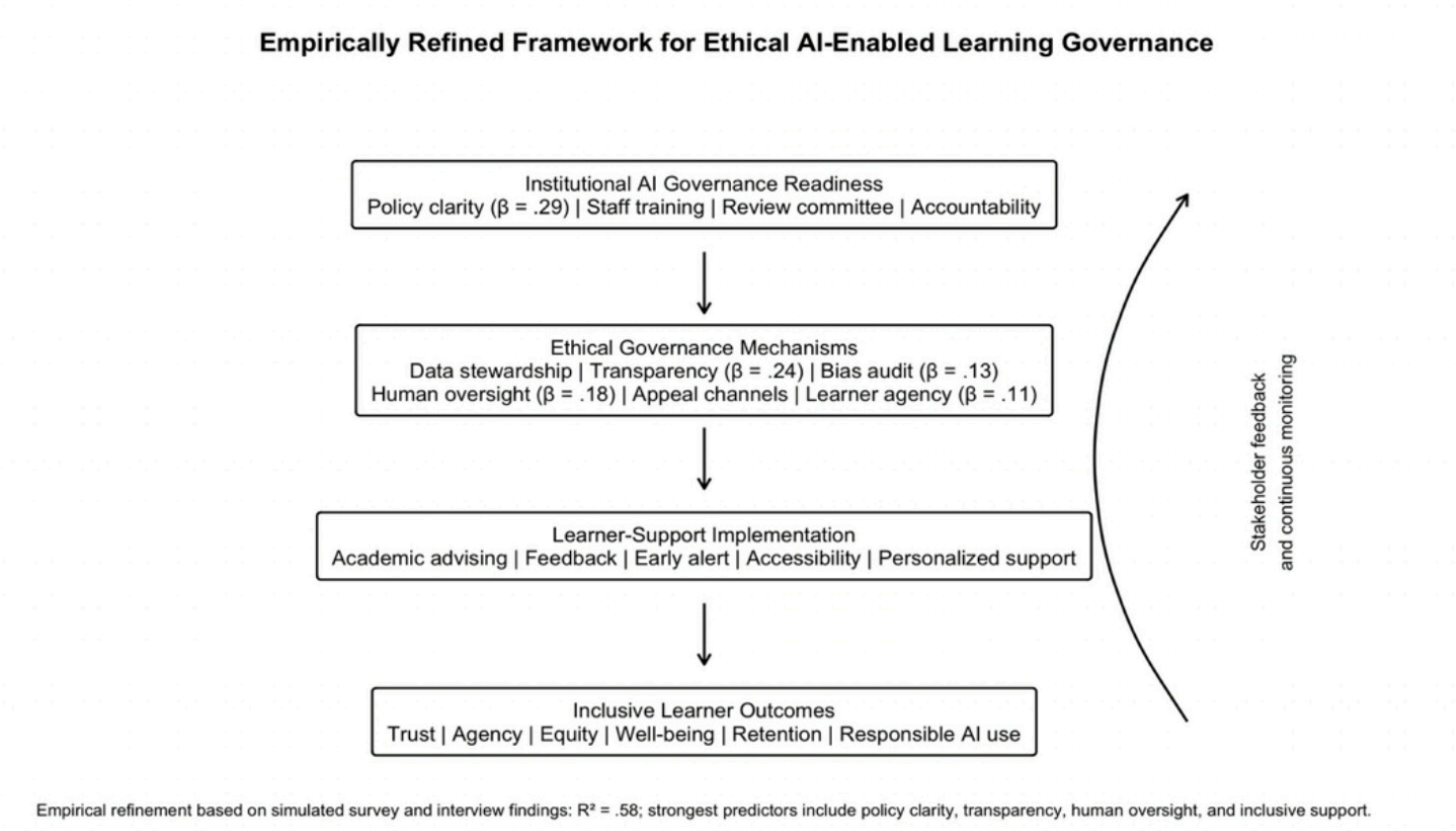


Figure 3

Empirically refined framework for ethical AI-enabled learning governance in Chinese higher education

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Appendix.docx