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Determinants of lecturer readiness to adopt generative AI in higher education: survey evidence from UTAUT and self-determination theory

Yujuan Luo[1] · Michael James Day[2]

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Abstract
Generative artificial intelligence (GAI) is reshaping higher education, yet lecturers' readiness remains under-examined. This study integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) with Self-Determination Theory (SDT) and individual attributes (AI literacy, teaching values, personal innovativeness) to explain lecturers' behavioural intention and GAI use. A cross-sectional survey of 651 university lecturers in mainland China measured UTAUT constructs (performance expectancy, effort expectancy, social influence, facilitating conditions), SDT needs (autonomy, competence, relatedness), and individual attributes. Confirmatory factor analysis and covariance-based structural equation modelling assessed measurement quality and structural paths; bootstrapped mediation tested indirect effects via intention, and latent-interaction moderation examined whether SDT strengthened antecedent–intention links. SDT was the strongest predictor of intention; UTAUT constructs were also significant. Teaching values and personal innovativeness showed positive effects, and AI literacy was positively associated with use/intention, which strongly predicted use, with facilitating conditions and SDT also showing direct effects. Findings conclude the value of professional development in Technology Enhanced Learning (TEL) that builds faculty AI literacy and competence, which supports autonomy and collegial relatedness, and must be underpinned by reliable institutional infrastructures to accelerate responsible GAI integration.

Keywords Generative Artificial Intelligence (GAI) · Higher Education · UTAUT · Self-Determination Theory (SDT) · Lecturer Readiness

Extended author information available on the last page of the article

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1 Introduction

Generative artificial intelligence (GAI) is increasingly embedded in higher education (HE), reshaping academic practices. While policy discourse and institutional strategies often emphasise AI's transformative potential, its educational impact depends considerably on how lecturers integrate AI tools effectively into teaching and curriculum shape. Lecturers act as key gatekeepers, then, in technology adoption, shaping pedagogical practices, modelling responsible use, and influencing students' development of AI-related competencies relevant to graduate employability (Selwyn, 2019; Zawacki-Richter et al., 2019; Bankins et al., 2024). China provides a salient context for examining lecturers' readiness for GAI adoption. National initiatives, including the Ministry of Education's (MOE) recent AI action plans, position AI and generative technologies as central to educational reform and workforce development (Knox, 2024; Day, 2025b). However, empirical studies suggest that implementation remains uneven. Many lecturers report limited professional development, uncertainty around ethical use, and insufficient institutional guidance, despite growing expectations to integrate AI into teaching (Fu & Li, 2024; Chiu et al., 2023; Day, 2025a). Existing research on AI adoption in HE has often focused on students or examined acceptance using general technology acceptance models, weighted towards Western contexts (Habibi et al., 2023; Strzelecki, 2024).

To address these gaps, this study integrates the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) with Self-Determination Theory (SDT; Ryan & Deci, 2017), alongside individual attributes relevant to GAI-integrated pedagogy. UTAUT captures expectancy-based beliefs and organisational conditions influencing adoption, while SDT explains how psychological need fulfilment, autonomy, competence, and relatedness, supports internalisation and sustained engagement. In addition, individual attributes including AI literacy, teaching values, and personal innovativeness are incorporated to reflect educators' capability resources, pedagogical identity, and openness to experimentation.

Accordingly, this study addresses the following research questions:

- **RQ1**: How do UTAUT constructs (performance expectancy, effort expectancy, social influence, facilitating conditions) influence lecturers' behavioural intention to adopt GAI?
- **RQ2**: How do SDT psychological needs and individual attributes (AI literacy, teaching values, personal innovativeness) shape lecturers' behavioural intention and actual GAI use?
- **RQ3**: Does behavioural intention mediate the relationships between these antecedents and actual GAI use?
- **RQ4**: Does SDT-based motivation moderate the relationships between UTAUT constructs and lecturers' behavioural intention?

By focusing on lecturers and integrating acceptance, motivation, and individual capability perspectives, this study contributes theoretically by extending UTAUT with motivational and pedagogical dimensions, and practically by offering evidence to inform professional development and institutional support strategies for responsible and equitable GAI adoption in HE. This study contributes insight in three ways. First, it integrates UTAUT with Self-Determination Theory to explain lecturers' readiness to adopt generative AI as both a cognitive and motivational process, thereby demonstrating that psychological need fulfilment significantly strengthens traditional technology acceptance pathways. Second, it extends adoption research by incorporating focus of AI literacy, teaching values, and personal innovativeness, demonstrating lecturers' engagement with generative AI depends not only on intention but also on professional capability, pedagogical alignment, and openness to experimentation. Third, the findings advance teaching practice and institutional strategy by showing that effective generative AI adoption requires more than encouraging use. It concludes by positioning recommendations showcasing that universities must support lecturers' autonomy, competence, and relatedness, strengthen AI literacy, and provide enabling institutional conditions to foster sustainable and responsible teaching innovation.

2 Literature review

There is a need to drive exploration of what AI competencies are required to do this effectively and in a manner that can enhance student experience (Selwyn, 2019; Zawacki-Richter et al., 2019; Day, 2025b). Therefore, understanding faculty readiness remains pivotal, because educators play a central role in determining how students engage with AI, as part of their broader learning and wellbeing experiences (Advance HE, 2023; 2024; Day, 2023).

2.1 Lecturer readiness for GAI in higher education

Lecturer readiness for educational technology adoption extends beyond technical competence to encompass pedagogical adaptation, ethical awareness, and institutional support (Lukin et al., 2022). In the context of GAI, readiness is particularly consequential because lecturers shape how AI is framed, legitimised, and used within teaching practices, influencing students' learning experiences and long-term employability (Welch, 2024; Xia, 2022; Xu, 2022; Zawacki-Richter et al., 2019; Bankins et al., 2024). Despite growing institutional emphasis on AI, lecturers often report uncertainty regarding appropriate pedagogical use, ethical boundaries, and assessment implications (Chaudhry & Kazim, 2021; Fu & Li, 2024). Universities have been suggested to frequently prioritise policy responses focused on preventing misuse, such as plagiarism, rather than supporting educators to model responsible and pedagogically meaningful AI integration, which impacts the student experience and creates confusion amongst students (Ryan, 2004; Williams, 2011; Selwyn, 2019; Zeide, 2019). As a result, adoption patterns are uneven: some lecturers engage experimentally as early adopters, while others avoid GAI due to concerns about deskilling, workload, or professional identity (Srinivasan, 2021; Zawacki-Richter et al., 2019). Understanding lecturers' readiness, therefore, requires theoretical frameworks that capture not only perceptions of technology but also motivational and contextual conditions shaping professional practice (Bian, 2024; Farrelly, 2023; Lin, 2020; Sage, 2025).

2.2 Technology acceptance: The UTAUT perspective

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a well-established framework for examining adoption of digital technologies (Venkatesh et al., 2003). It identifies four core determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs have been applied in educational technology research to predict behavioural intention and use adoption (Williams et al., 2015; Xue et al., 2024). In teaching contexts, UTAUT is relevant because lecturers' adoption decisions are embedded within organisational structures and professional norms. Performance expectancy, therefore, reflects beliefs that GAI can enhance teaching effectiveness, while effort expectancy concerns the perceived ease of integrating GAI into pedagogical workflows. Social influence, meanwhile, captures perceived expectations from colleagues and institutional leadership, and facilitating conditions reflect access to infrastructure, training, and policy support. Prior research suggests that facilitating conditions and social influence may be especially salient for lecturers (Marks & Thomas, 2022; Rahiman & Kodikal, 2024). However, UTAUT primarily emphasises cognitive evaluations and external conditions, offering limited insight into why educators persist in adoption when experimentation involves uncertainty and professional risk.

2.3 Motivational foundations: self-determination theory

Self-Determination Theory (SDT) offers some mediation to this, and addresses this limitation by explaining how motivation is internalised and sustained through fulfilment of three psychological needs: autonomy, competence, and relatedness (Ryan & Deci, 2017, 2020). In educational technology contexts, SDT highlights that adoption is more likely when educators feel volitional and socially supported in the process. SDT complements UTAUT conceptually, then, so is used within this research to create a mutually complemented research toolkit. While effort expectancy captures perceived operational ease, SDT competence reflects a broader sense of mastery and professional efficacy. Social influence reflects perceived expectations, whereas SDT relatedness concerns supportive professional relationships. Facilitating conditions describe external resources, while SDT autonomy captures whether engagement is experienced as self-endorsed rather than imposed. Empirical studies demonstrate that SDT-related motivation strongly predicts intention to use AI and can amplify the effects of expectancy (Bergdahl et al., 2023; Hsu, 2023; Zheng et al., 2024). This suggests that lecturers may recognise the usefulness of GAI yet remain reluctant to adopt it if their psychological needs are not supported; SDT, therefore, provides a critical motivational lens for understanding lecturers' readiness.

2.4 Individual attributes relevant to GAI adoption

In addition to acceptance and motivation, lecturers' readiness for GAI-integrated teaching is shaped by individual attributes that capture capability, pedagogical identity, and openness to innovation. Three attributes are particularly salient across literature and studies therein. First, AI literacy encompasses educators' ability to understand, evaluate, and ethically apply GAI tools in teaching, hence must be explored in terms of institutional conditions building that literacy (Mah & Groß 2024; Wang et al. 2025a, 2025b). While distinct from effort expectancy and perceived competence, AI literacy reflects substantive knowledge required to judge output quality, bias, and pedagogical appropriateness. Therefore, second, teaching values represent lecturers' normative beliefs about pedagogical integrity, assessment fairness, and the legitimacy of technology use in their teaching (Sitar-Taut & Mican, 2021; Foroughi et al., 2024). Unlike social influence, teaching values reflect internalised professional standards that can enable or constrain adoption even when usefulness is acknowledged, and as such are unique, personal and case specific. Third, personal innovativeness captures a dispositional openness to experimentation with new technologies (Agarwal & Prasad, 1998). This trait, then, is especially relevant in emergent domains such as GAI, where norms and institutional guidance are still evolving (Pesovski et al., 2024). Together, these attributes explain variance in lecturers' readiness that cannot be fully accounted for by acceptance beliefs or motivational states alone.

2.5 Conceptual integration and research model

Drawing on these strands, this study conceptualises lecturers' readiness for GAI adoption as a multi-layered process. UTAUT provides the expectancy-based and contextual foundation of adoption, SDT explains motivational internalisation and persistence, and individual attributes capture capability, pedagogical alignment, and openness to innovation. Behavioural intention is positioned as the central mediator translating beliefs, motivation, and attributes into actual use, while SDT is further theorised to moderate the strength of expectancy–intention relationships. This integrated framework responds directly to calls for more theory-driven, faculty-focused research on AI adoption in HE (Zawacki-Richter et al., 2019; Crompton & Burke, 2023). Hence, our integrated approach provides a coherent basis for the hypotheses tested in this study. Students' experiences reflect AI unevenness, with those studying in elite universities suggested to gain more benefits and see AI's potential stronger, but overall awareness remains only moderate amongst Chinese learners (Li et al., 2025). Lecturers are reported in studies as worrying about cheating, and other forms of misuse, showing tension between national policy and everyday practice, and constant focus of misuse as a common language around AI technologies (Fu & Li, 2024; Chiu et al., 2023). If staff and students alike identify feeling pushed to adopt AI without proper training, this indicates further need for critical investigation (Knox, 2024), as research points to growing efforts to share good practice, deal with ethical concerns and strengthen staff capacity (Xu & Ouyang, 2022). This makes it important to ask how lecturers see their own readiness to use GAI and what conditions make adoption fair and effective. The subsequent summary of the landscape, then, is outlined in Table 1:

Table 1 Conceptual framework: construct definitions and theoretical distinctions

Theoretical Framework	Construct	Definition	Differentiated from	Key references
UTAUT	Performance Expectancy	Perceived usefulness of GAI for enhancing teaching effectiveness	Motivational quality; self-efficacy; values	Venkatesh et al. (2003)
	Effort Expectancy	Perceived ease of learning and operating GAI tools	AI literacy; SDT competence	Venkatesh et al. (2003)
	Social Influence	Perceived normative expectations from significant others	Teaching values; SDT relatedness	Venkatesh et al. (2003)
	Facilitating Conditions	Perceived availability of institutional resources, infrastructure, and support	SDT autonomy; personal capability	Venkatesh et al. (2003)
SDT	Autonomy	Perceived volition and self-endorsement in adoption decisions	Facilitating conditions; social influence	Ryan and Deci (2000, 2017)
	Competence	Perceived effectiveness and mastery in GAI use	Effort expectancy; AI literacy	Ryan and Deci (2000, 2017)
	Relatedness	Perceived sense of belonging and interpersonal support	Social influence	Ryan and Deci (2000, 2017)
Capability Resources	AI Literacy	Knowledge and skills to evaluate and use GAI responsibly and ethically	Effort expectancy; SDT competence	Wang et al. 2025a, 2025b; Mah and Groß (2024)
Pedagogical Identity	Teaching Values	Normative beliefs regarding pedagogical integrity and appropriate technology use	Social influence	Sitar-Tăut & Mican (2021); Foroughi et al. (2024)
Dispositional Openness	Personal Innovativeness	Trait-based propensity to experiment with new technologies	UTAUT beliefs; SDT psychological states	Agarwal and Prasad (1998); Pesovski et al. (2024)

3 Methodology

Readiness can thus be investigated amongst lecturers through an 'investigatory mix' exploring cognitive appraisals (UTAUT), motivation (SDT) and individual traits such as AI literacy, teaching values and openness to change. Doing so helps identify what barriers remain, and where policy and training are weak. China's strong national ambitions clash with patchy local practice, leaving clear gaps in educator preparedness and student outcomes, as well as shortfalls in original and novel insight, which this article seeks to address by reporting findings of a study enacted to investigate lecturer readiness to use GAI.

3.1 Instruments and participants

Institutional support and professional development are widely recognised as critical enablers of AI readiness. Universities that invest in AI literacy programmes, clear guidelines, and supportive cultures are more likely to achieve effective AI integration (Lukin et al., 2022). Building on this premise, the present study employed a quantitative research design to investigate factors influencing university lecturers' readiness to integrate generative AI (GAI) into HE classroom practices in mainland China. Unlike much existing research that foregrounds student perspectives, this study focused specifically on educators' acceptance, readiness, and determinants of GAI use. This study surveyed university lecturers from a range of institutions across mainland China to capture diversity in discipline, teaching experience, and prior exposure to generative AI (GAI). The final sample comprised 651 classroom-focused lecturers with varying degrees of familiarity with GAI. The Unified Theory of Acceptance and Use of Technology (UTAUT) was adopted as the primary framework, given its established utility for studying technology adoption (Venkatesh et al., 2003). UTAUT highlights performance expectancy, effort expectancy, social influence, and facilitating conditions as predictors of behavioural intention and technology uptake. While UTAUT has been widely applied in educational contexts (Da Silva Soares et al., 2025; Xue et al., 2024), its application to GAI adoption among teachers in China remains limited. Moreover, critiques suggest UTAUT may overlook intrinsic motivational processes (Williams et al., 2015). To address this, the study integrated Self-Determination Theory (SDT) and additional individual attributes, thereby extending the framework to capture both extrinsic and intrinsic determinants of adoption.

3.2 Ethical approval

The study protocol, ethics and approach was reviewed and approved through an institutional review board (ID ER-LRR-11000128120240606102842) at the first-author's university. All participants provided informed consent, participation was voluntary, and data were anonymised to ensure confidentiality.

3.3 Theoretical framework

The research was guided by a conceptual framework integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) and Self-Determination Theory (SDT), alongside individual attributes relevant to GAI-integrated pedagogy. UTAUT (Venkatesh et al., 2003) conceptualises adoption through expectancy-based beliefs and contextual enablers: *performance expectancy* (belief that GAI enhances job performance), *effort expectancy* (perceived ease of GAI use), *social influence* (perception of peer or institutional expectations), and *facilitating conditions* (availability of technical and organisational support). Meanwhile, SDT (Ryan & Deci, 2017, 2020) complements this by explaining the motivational internalisation of adoption through fulfilment of psychological needs: *autonomy* (sense of volition and choice), *competence* (sense of efficacy in using GAI), and *relatedness* (connection with others during GAI adoption), which supports sustained engagement when teachers must experiment and redesign pedagogy. In addition, several individual attributes were factored, and three micro-level variables capture variance beyond acceptance beliefs and need fulfilment in a rapidly evolving domain. First, *personal innovativeness* (PI), so the willingness to experiment with new technologies (Agarwal & Prasad, 1998). Second, *teaching values* (TV), so the perceived pedagogical utility and efficiency of educational tools (Sitar-Taut & Mican, 2021). Third, *AI literacy (AL)*, encompassing awareness, usage, evaluation, and ethical considerations in AI adoption (Wang et al. 2025a, 2025b). These attributes enabled examination of how personal orientations and pedagogical values intersect with broader acceptance and motivational constructs.

3.4 Participants and sampling

The target population comprised lecturers working in universities across mainland China. Using convenience sampling, 651 lecturers were recruited through university colleagues, departmental mailing lists, and WeChat-based academic groups, enabling access to lecturers across a range of disciplines, teaching experience, and prior exposure to GAI tools within a shared professional context of institutional and formal teaching. A total of 651 lecturers completed the online survey (Table 2). Because recruitment combined network-based and group dissemination, the total number of lecturers who received the invitation could not be precisely determined; however, the sample profile is largely representative and reported in Table 1 to document participant characteristics and variation in GAI readiness. The sample was predominantly

Table 2 Participant characteristics

Variable	Category	Frequency	Percentage (%)
Gender	Male	236	36.25
	Female	415	63.75
Teaching experience	1–3 years	78	11.98
	4–6 years	139	21.35
	7–10 years	207	31.80
	10–15 years	115	17.67
	Over 15 years	112	17.20
Institution type	Public university	361	55.45
	International university	290	44.55
Language of instruction	Chinese	519	79.72
	English	132	20.28
Discipline	Natural sciences	94	14.44
	Humanities	151	23.20
	Social sciences	154	23.66
	Engineering and technology	115	17.67
	Medicine	40	6.14
	Education	75	11.52
	Arts	22	3.38
Frequency of GAI use	Daily	105	16.13
	Several times per week	255	39.17
	Several times per month	151	23.20
	Rarely	122	18.74
	Never	18	2.77
Total		651	100.00

Percentages may not sum to exactly 100 due to rounding. International university refers to Sino-foreign cooperative or internationalised institutions operating in mainland China female and represented a wide range of teaching experiences. GAI use was common with 55.30% reported using GAI daily or several times per week while 21.51% used it in a limited manner, indicating meaningful variation in adoption experience.

3.5 Survey instrument & data collection

The survey instrument included validated scales for UTAUT constructs (Venkatesh et al., 2003, 2012), SDT psychological needs (Standage et al., 2005; Ryan & Deci, 2017), and individual attributes (Agarwal & Prasad 1998; Sitar-Taut & Mican 2021; Wang et al. 2025a, 2025b). Items were adapted to the GAI-integrated teaching context by rewording items to reference to GAI use for teaching (e.g. lesson planning, feedback, assessment support) while preserving the original construct meaning. The adapted items were reviewed for clarity and contextual relevance and refined through a pilot test with 20 lecturers (12 female, 8 male) to evaluate item clarity, response burden, and construct coverage, resulting in minor wording adjustments prior to full deployment. The questionnaire was administrated in Chinese. Items originally developed in English were translated using a standard forward–back translation procedure by bilingual researchers. Discrepancies were resolved through iterative discussion to ensure sematic equivalence and alignment with the intended construct definitions. The pilot test further confirmed item comprehensibility and appropriateness in the target context. Items were measured using five-point Likert scales (1 = strongly disagree to 5 = strongly agree). Data from participants was collected via structured online surveys. To ensure data completeness and minimise missing data, the survey platform required all items to be answered before submission; as a result, the final valid sample comprised 651 fully completed questionnaires without item-level missing data. Completed responses were screened for response quality (e.g., unusually short completion times and patterned responding), and retained cases met the research's inclusion criteria. To reduce potential common method bias, several procedural steps were taken. Participants were voluntary and anonymous, and informed consent was obtained electronically prior to survey completion. Respondents were informed there were no right or wrong answers, which helps reduce evaluative apprehension and socially desirable responding. Besides, predictor and criterion constructs were presented in separate blocks with clear construct labels to minimise interpretive overlap.

Because all constructs were measured through self-report within a single survey, the potential common method bias was assessed using Harman's single-factor test and collinearity diagnostics (tolerance and variance inflation factor; VIF). Harman's test provides an initial indication of whether a single general factor accounts for the majority of covariance among items, while tolerance/VIF help identify whether common-source inflation may be present through problematic collinearity. Hence, the analytical strategy employed covariance-based structural equation modelling (CB-SEM) using AMOS 26, chosen for its ability to test complex relationships among latent variables. First, confirmatory factor analysis (CFA) was conducted to assess measurement validity and reliability. Second, the hypothesised relationships were tested through SEM, complemented by mediation analysis (bootstrapping) and moderation testing to evaluate the role of motivation (SDT) in strengthening or weakening UTAUT–intention–behaviour pathways, consistent with the proposition that psychological need fulfilment supports motivation internalisation of adoption decisions (Ryan & Deci, 2017, 2020; Shen et al., 2024; Zheng et al., 2024).

3.6 Hypothesis formation

Hypotheses were derived deductively from UTAUT and SDT, with individual attributes included to capture capability, pedagogical identity, and openness to innovation (Table 1; Fig. 1). UTAUT predicts intention and behaviour through expectancy beliefs and enabling conditions, while SDT explains why teachers internalise adoption and persist through skill development and institutional implementation。 Drawing on the research questions articulated in the introduction above, and articulated into a research process within this study, a series of hypotheses were created to test the survey data gained through the research methodology described above:

3.6.1 Hypotheses related to the original UTAUT model

UTAUT proposes that behavioural intention is shaped by performance expectancy, effort expectancy and social influence, while enacted behaviour is supported by behavioural intention and facilitating conditions (Venkatesh et al., 2003). Accordingly:

- H1: Lecturers' behavioural intention (BI) positively predicts their use behaviour (UB) of GAI.
- H2: Facilitating conditions (FC) positively predict lecturers' UB of GAI.
- H3: Performance expectancy (PE) positively predicts lecturers' BI to use GAI.
- H4: Effort expectancy (EE) positively predicts lecturers' BI to use GAI.
- H5: Social influence (SI) positively predicts lecturers' BI to use GAI.

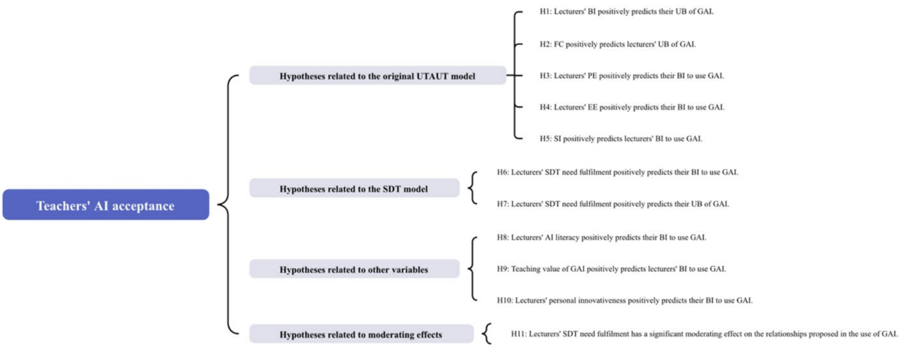

Fig. 1 Proposed research model and hypotheses. *Note.* PE= performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; SDT = self-determination theory; AL = AI literacy; TV= teaching values; PI = personal innovativeness; BI = behavioural intention; UB= use behaviour

3.6.2 Hypotheses related to the SDT model

SDT posits that adoption is more likely to be internalised and sustained when lecturers fulfil psychological needs through autonomy, competence, and relatedness in the adoption process (Ryan & Deci, 2017, 2020). Therefore:

- H6: Lecturers' self-determination theory (SDT) psychological need fulfilment positively predicts their BI to use GAI.
- H7: Lecturers' SDT psychological need fulfilment positively predicts their UB of GAI.

3.6.3 Hypotheses related to other variables

As discussed, GAI adoption in teaching and supporting student learning requires responsible capability, pedagogical legitimacy, and openness to experimentation, additional hypotheses are proposed that lecturer attributes explain variance in intention beyond UTAUT and SDT. Hence:

- H8: Lecturers' AI literacy (AL) positively predicts their BI to use GAI.
- H9: Teaching values (TV) positively predict lecturers' BI to use GAI.
- H10: Lecturers' personal innovativeness (PI) positively predicts their BI to use GAI.

3.6.4 Hypotheses related to moderating effects

SDT further suggests that expectancy beliefs are more likely to translate into intention when adoption is psychologically supported. Therefore, we hypothesise that SDT need fulfilment strengthens key UTAUT constructs and behavioural intention. Accordingly:

- H11: Lecturers' SDT need fulfilment has a significant moderating effect on the relationships proposed in the use of GAI.

3.7 Data analysis & triangulation

Data were collected via an online structured survey provided with a link and participant information, as well as right to withdraw. A pilot study from one randomly selected university informed instrument refinement in the initial stages, providing a baseline for engagement. The final survey was then distributed across public and private universities to ensure variation in institutional context, with the total number of participants amalgamated into one specific grouping to avoid re-identification risks, whether of the participants themselves, or of their universities. This was considered in line with China's national emphasis on technological innovation, this setting offered valuable insight into how socioeconomic, sociocultural, and institutional factors shape lecturers' readiness for GAI integration. Equally, we wanted to recognise some faculty may be concerned that their views might reflect negatively on their institutions, creating duress, and hence did not seek to codify or identify based on university, region or geography, focusing instead overall on 'lecturers'. The instruments were triangulated, as they measured UTAUT constructs, SDT psychological needs, and exploratory controls as detailed earlier (Sagnier et al. 2020; Standage et al. 2005; Venkatesh et al. 2012; Wang et al. 2023a, 2025b). Items were rated on five-point Likert scales, providing scope of agreement. Covariance-based Structural Equation Modelling (CB-SEM) was employed to assess direct and indirect effects among latent variables, chosen for its suitability in testing complex relationships involving both reflective and formative constructs. Mediation analysis (bootstrapping) and moderation tests were also undertaken to evaluate the role of motivation (SDT) in shaping links between UTAUT predictors, behavioural intention, and actual use of GAI. Ethical protocols were strictly observed beyond the IRB. Participants were informed that participation was voluntary, provided consent, and were assured confidentiality through anonymisation. These measures supported a rigorous, theory-driven analysis of the multidimensional factors influencing lecturers' readiness for GAI adoption in Chinese HE.

To test the research hypotheses, the study employed structural equation modelling (SEM), selected for its ability to control measurement error and estimate mediating and moderating effects with precision. Data analysis was conducted using SPSS and IBM AMOS 26, following Kline's (2023) guidelines. Model fit was assessed using standard indices: comparative fit index (CFI) and Tucker–Lewis index (TLI) values above 0.9, chi-square to degrees of freedom ratio (χ^2/df) below 3, and root mean square error of approximation (RMSEA) between 0.05 and 0.08. These benchmarks confirmed the suitability and predictive power of the proposed model. After establishing measurement validity (convergent and discriminant), path significance was examined using CB-SEM. Moderation analyses were then conducted to explore the role of motivation and demographic variables. Exploratory factor analysis (EFA) was also performed in SPSS to evaluate construct validity. Principal axis factoring with varimax rotation produced satisfactory loadings, with a Kaiser–Meyer–Olkin (KMO) value of 0.948 indicating excellent sampling adequacy. Bartlett's sphericity test was significant ($p<0.001$), confirming factorability. The extracted factors explained 65.72% of total variance. Confirmatory factor analysis (CFA) further validated the measurement model, with items below the threshold loading of 0.5 removed (Hair et al., 2019). Results are reported in the following section.

4 Findings

4.1 CFA results

Prior to testing the structural relationships among the key constructs, confirmatory factor analysis was conducted to verify the relationships between latent factors and their observed variables, assessing the extent to which these relationships align with the theoretical expectations. CFA was conducted using AMOS 26 to evaluate the structural validity of the scale and determine the structural appropriateness for the subsequent structural equation modelling (SEM). Model fit indices supported the robustness of the measurement model to the data. The chi-square to degrees-of-freedom ratio ($\chi^2/df = 1.679$) was below the recommended threshold of 3. Goodness-of-Fit Index (GFI = 0.904). Adjusted Good-of-Fit Index (AGFI = 0.892), Normed Fit Index (NFI-0.913), Tucker-Lewis Index (TLI = 0.960), and Comparative Fit Index (CFI = 0.963) all surpassed the commonly accepted threshold values, indicating a strong fit (Appendix: Table 10). Additionally, the Root Mean Square Error of Approximation (RMSEA = 0.032) was substantially lower than the basic acceptable maximum of 0.08, reflecting minimal model misfit (Gallagher & Brown, 2013). Descriptive analysis further confirmed that there were not strong floor or ceiling effects based on the mean calculation of individual items (Table 11 in Appendix). In addition, the correlation matrix among the constructs is also presented (Table E in Appendix). Normality testing suggests that the data exhibits a normal distribution. Specifically, the absolute skewness magnitudes, ranging from 0.457 to 1.029, are considered acceptable for large samples (Kline, 2023). All kurtosis values fell within the range −0.51 to + 1.03, indicating no serious issues with peakedness or flatness of the distribution, though we note that multivariate normality was not directly tested as AMOS assumes multivariate normality (Cain et al., 2017). Thus, the data can be considered sufficient for parametric analysis, especially given the robustness of such methods with large sample sizes, as summarised in Table 11 (Appendix).

In addition, the standardised factor loadings ranged from 0.671 to 0.901, all exceeding the recommended threshold of 0.6, indicating strong measurement validity (Hair et al., 2019). All loadings were statistically significant ($p < 0.001$), confirming each observed variable reliably measures its corresponding latent factor. The Cronbach's alpha values, ranging from 0.807 to 0.952, confirm satisfactory internal reliability of the measurement (see Table 9 in Appendix). Moreover, the assessment of convergent validity and divergent validity was carried out to further validate the measure models of the proposed framework. Further, Harman's single-factor test indicated that the first factor accounted for 30.395% of the total variance, which is below the commonly used 40% threshold, suggesting common method bias is not pronounced (Harman, 1967; Podsakoff et al., 2003). Collinearity diagnostics further supported this conclusion: tolerance values ranged from 0.324 to 0.785 m and VIF values from 1.274 to 3.086, with all VIF values below the conservative threshold of 3.3 (Table 12 in Appendix).

Methodologically, convergent validity and divergent validity are commonly tested for construct validity (Table 3). The convergent validity assesses whether constructs that are theoretically related exhibit the anticipated relationship, while divergent validity scrutinises whether constructs theorised as unrelated genuinely show no connection. Convergent validity was established through the Average Variance Extracted (AVE) values and Composite Reliability (CR) indices. The AVE values ranged from 0.573 to 0.679, surpassing the recommended benchmark (Fornell & Larcker, 1981). The CR values varied from 0.808 to 0.952, exceeding the acceptable threshold of 0.7, confirming excellent internal consistency (Hair et al., 2019). The authors note that CR is generally considered a more robust measure, but Cronbach's alpha is included for research transparency. Discriminant validity was ensured, as the square root of AVE for each construct was greater than the highest correlation between that construct and any other construct in the model (Fornell & Larcker, 1981). Specifically,

Table 3 Average variance extracted and composite reliability for each construct

Factor	AVE	CR
SDT	0.573	0.952
PE	0.647	0.880
EE	0.634	0.874
SI	0.584	0.808
FC	0.594	0.854
PI	0.618	0.828
TV	0.593	0.853
AL	0.606	0.925
BI	0.631	0.837
UB	0.679	0.864

AVE average variance extracted; *CR* composite reliability

Table 4 Discriminant validity assessment using the Fornell-Larcker criterion

Factor	SDT	PE	EE	SI	FC	PI	TV	AL	BI	UB
SDT	0.757									
PE	0.206	0.805								
EE	0.186	0.463	0.796							
SI	0.179	0.501	0.502	0.764						
FC	0.213	0.574	0.532	0.487	0.771					
PI	0.131	0.489	0.445	0.577	0.446	0.786				
TV	0.137	0.552	0.509	0.581	0.530	0.529	0.770			
AL	0.205	0.525	0.515	0.564	0.527	0.511	0.507	0.778		
BI	0.445	0.606	0.588	0.615	0.618	0.585	0.645	0.607	0.794	
UB	0.402	0.348	0.296	0.341	0.436	0.282	0.366	0.383	0.571	0.824

Diagonal values (in bold) are the square roots of AVE for each construct. Off-diagonal values are inter-construct correlations. Discriminant validity is indicated when the square root of AVE for each construct exceeds its correlations with other constructs

the square roots for SDT (0.757), PE (0.805), EE (0.796), SI (0.764), FC (0.771), PI (0.786), TV (0.770), AL (0.778), BI (0.794) and UB (0.824) were all higher than the respective highest inter-construct correlations, indicating sufficiently good discriminant validity (Table 4). The reliability and convergent validity indices and discriminant validity methodologically support measurement quality and construct distinctiveness, ensuring conceptual separation among UTAUT, SDT and individual attribute constructs. Overall, the CFA demonstrated robust measurement properties and model fit, confirming that the data structure adequately represents the underlying theoretical constructs. This model is therefore suitable for further analysis through structural equation modelling (SEM).

4.2 Descriptive and correlation analysis

As indicated in the table below, the participants reported moderately positive perceptions regarding PE (M=3.70, SD=1.03), EE (M=3.73, SD=0.91), SI (M=3.65, SD=1.06), PI (M=3.63, SD=0.85), and FC (M=3.80, SD=0.92). Notably, the perceived TV (M=3.95, SD=0.87) and BI (M=3.99, SD=0.92) towards using GAI are particularly strong, showing teachers' positive attitudes and perceptions. However, AI literacy (M = 3.60; SD = 0.93) and motivation as reflected via SDT (M = 3.48, SD = 0.83) and use behaviour (UB) (M = 3.61, SD = 1.03) show moderate scores, indicating variability in teachers' acceptance of employing GAI. This is summarised in Table 11 (see Appendix).

The correlation analysis revealed significant positive correlations among all variables. In fact, the highest correlation was observed between UB and BI (r=0.571, p<0.01), suggesting a strong relationship between lecturers' intentions and actual usage of GAI. Other variables, including FC (r=0.436), AL (r=0.382), TV (r=0.366), PE (r=0.348), and SI (r=0.341), also showed significant positive correlations with UB (p < 0.01). In addition, BI demonstrated substantial positive links with PE (r=0.606), SI (r=0.615), FC (r=0.618), TV (r=0.645), and AL (r=0.597). However, motivation had relatively weaker but still significant correlations with UB (r=0.402) and BI (r=0.445), indicating moderate influence from lecturers' psychological readiness for the GAI adoption. Such insights are outlined in Table 13 (Appendix), Tables 3 and 4 below. Within Table 4, all constructs satisfy discriminant validity, which strengthens the measurement model robustness, and such findings are summarised in Fig. 2.

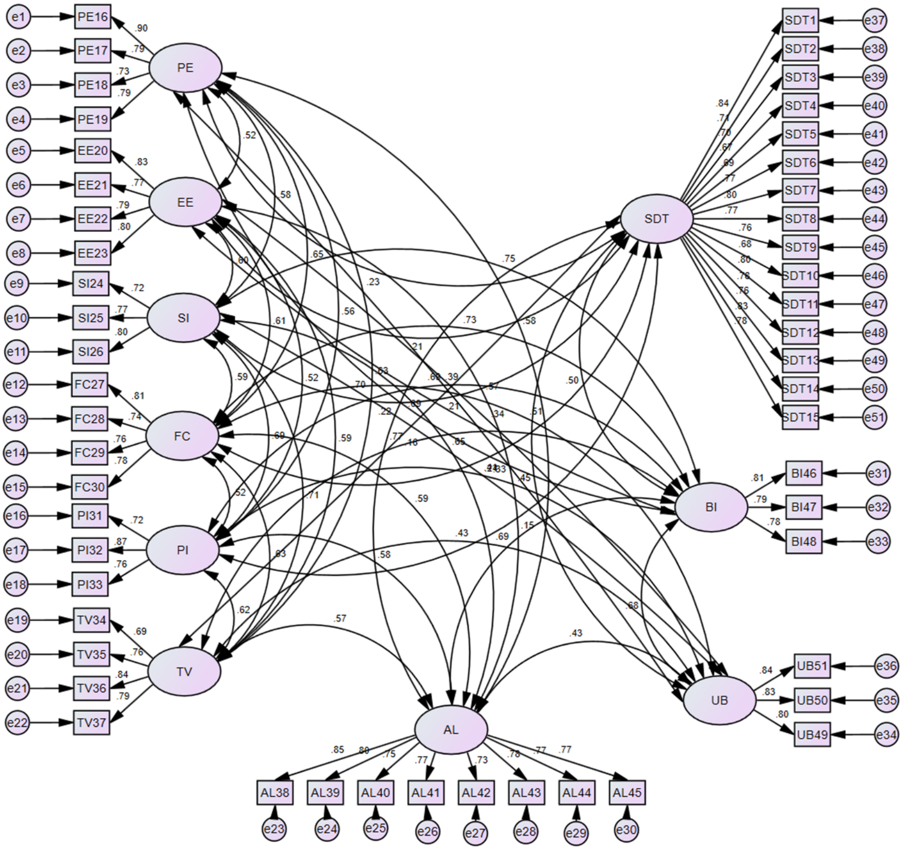

Fig. 2 Confirmatory factor analysis model for the measurement model. *Note.* Numbers indicate standardised factor loadings and inter-construct correlations

4.3 Structural equation modelling results

Prior to exploring the moderation effects of motivation, SEM analysis was carried out to explore learners' readiness for GAI tools in the HE context. Figure 3 presents both unstandardised and standardised estimates of the path coefficients in the model. In addition, the squared multiple correlations (R^2) of the endogenous variables (i.e., BI and AU), which signify the percentage of explained variance, were reported. The overall model fit was assessed using standard criteria based on the structural equation modelling: the ratio of Chi-square to degrees of freedom (χ^2/df), the Goodness-of-Fit Index (GFI), the Normed Fit Index (NFI), the Tucker-Lewis Index (TLI), the Comparative Fit Index (CFI), and the Root Mean Square Error of Approximation (RMSEA). As indicated in Table 14 (Appendix), the model demonstrates a strong model fit. The χ^2/dfvalue of 1.694 is below the cut-off of 3.0, indicating low model

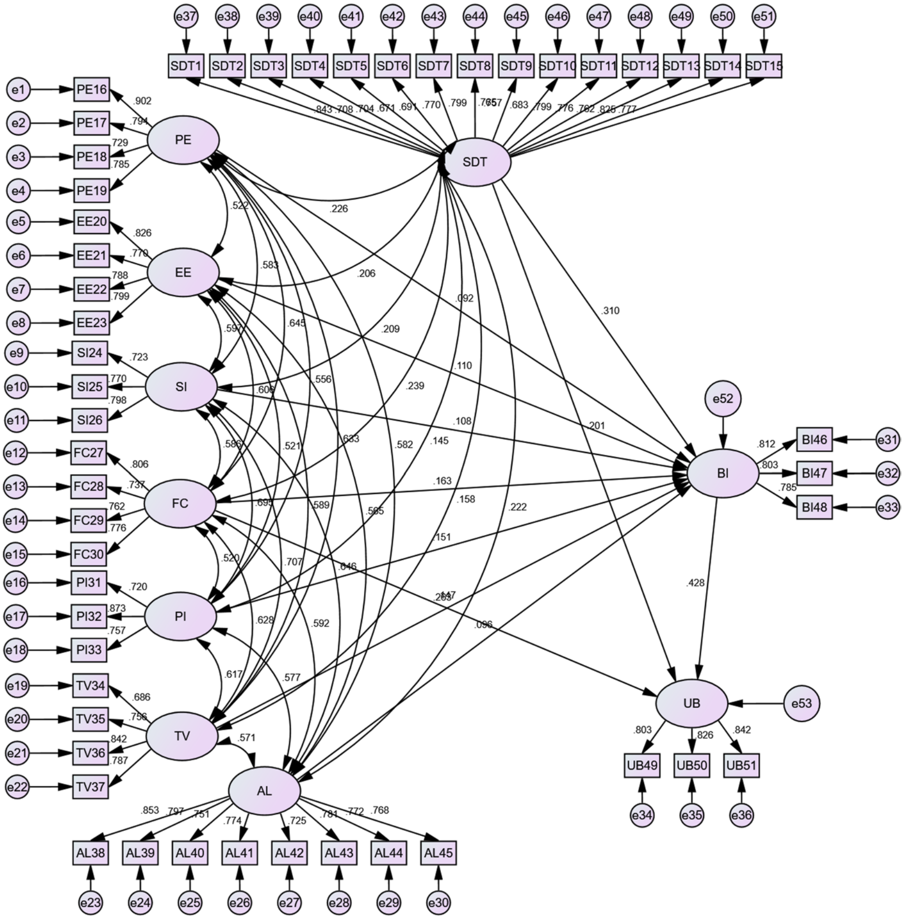

Fig. 3 Structural equation model with standardised path coefficients. *Note:* Values on paths indicate standardised regression coefficients. SEM illustrating standardised path coefficients and relationships among latent constructs. *Note.* Numbers indicate standardised path coefficients

misspecification (Kline, 2023). The GFI (0.903) and AGFI (0.891) exceed the acceptable threshold of 0.80, suggesting satisfactory absolute fit. The incremental fit indices, including NFI (0.911), TLI (0.959), and CFI (0.962), all surpass the 0.90 benchmark, demonstrating a substantial improvement in the proposed model relative to the baseline model. Additionally, the RMSEA value (0.032) was well below the acceptable upper limit of 0.08, further confirming the robust fit of the model (Hair et al., 2019). The path analysis results revealed significant relationships among the core constructs. Specifically, PE positive influenced BI (ß=0.076, S.E.=0.032, C.R.=2.332, $p=0.02$), indicating that lecturers' perceptions of GAI enhancing teaching performance significantly drive their intention to adoption it. EE demonstrated a stronger influence on BI (ß=0.115, S.E.=0.039, C.R.=2.918, $p=0.004$), suggesting the importance of perceived ease of use in the process of adoption. SI also positively influenced BI (ß=0.108, S.E.=0.053, C.R.=2.022, $p=0.043$), highlighting that external social expectations significantly affect teaches' intentions. FC significantly predicted BI (ß=0.16, S.E.=0.042, C.R.=3.775, $p<0.001$), emphasising the critical role of organisational and technical support. PI (ß=0.194, S.E.=0.055, C.R.=3.549, $p<0.001$) and TV (ß=0.318, S.E.=0.058, C.R.=5.461, $p<0.001$) showed highly significant positive impacts on BI, underscoring teachers' innovative tendencies and perceived educational benefits as key motivators. AL also positively affected BI (ß=0.088, S.E.= 0.035, C.R.= 2.542, $p=0.011$), indicating that higher AI literacy increases teachers' willingness to adopt GAI. SDT emerged as the strongest predictor of BI (ß=0.339, S.E.=0.03, C.R.=11.327, $P<0.001$), emphasising perceived autonomy, competence and relatedness as critical factors influencing teachers' willingness to use GAI. Regarding teachers' adoption behaviour (UB), FC (ß=0.154, S.E.=0.067, C.R.=2.298, $p=0.022$) and SDT ($\beta=0.235$, S.E.=0.051, C.R.=4.58, $p<0.001$) significantly predicted actual GAI use. BI had a particularly strong influence on UB (ß=0.457, S.E.=0.078, C.R.=5.866, $p<0.001$), demonstrating that lecturers' intentions strongly translate into actual usage. In sum, the SEM analysis confirmed multiple critical pathways influencing lecturers' intention and adoption behaviours regarding GAI use. Factors such as behavioural internation, facilitating conditions, psychological motivation (SDT), performance expectancy, and individual innovativeness were essential determinants in lecturers' adoption and integration of GAI into teaching practice. Such insights are consolidated across Table 13 in Appendix, Table 5, and Fig. 3 below.

4.4 Mediation analysis

To examine whether BI significantly mediates the relationships between PE, EE, SI, FC, TV, AL, SDT, and UB, the mediation analysis follows Hair et al.'s (2021) study, in which bootstrapping was used to assess the significance of indirect effects. The detailed mediation results are presented in (Table 6).

The above table indicated that BI significantly mediated the relationships between all investigated antecedents and UB. Specifically, UTAUT constructs (i.e., PE, EE, SI, FC) all demonstrated a significant and noteworthy indirect effect on UB through

Table 5 Structural model path estimates and hypothesis support

Structural path	Standardised coefficient (β)	Standard error (SE)	p-value	Hypothesis supported
BI ← PE	0.076	0.032	0.020	Yes
BI ← EE	0.115	0.039	0.004	Yes
BI ← SI	0.108	0.053	0.043	Yes
BI ← FC	0.160	0.042	<0.001***	Yes
BI ← PI	0.194	0.055	<0.001***	Yes
BI ← TV	0.318	0.058	<0.001***	Yes
BI ← AL	0.088	0.035	0.011	Yes
BI ← SDT	0.339	0.030	<0.001***	Yes
UB ← FC	0.154	0.067	0.022	Yes
UB ← SDT	0.235	0.051	<0.001***	Yes
UB ← BI	0.457	0.078	<0.001***	Yes

Standardised coefficients (β), standard errors (SE), and p values are reported. **p <.001

Table 6 Mediation effects via behavioural intention between antecedents and use behaviour

Mediation Pathway	Effect	Boot SE	Boot LLCI	Boot ULCI	z-value	p-value
PE → BI → UB	0.078	0.020	0.038	0.120	3.925	<0.001
EE → BI → UB	0.095	0.022	0.042	0.125	4.355	<0.001
SI → BI → UB	0.071	0.015	0.045	0.102	4.816	<0.001
PI → BI → UB	0.096	0.016	0.046	0.110	6.004	<0.001
FC → BI → UB	0.107	0.019	0.058	0.136	5.528	<0.001
TV → BI → UB	0.131	0.026	0.066	0.168	5.056	<0.001
AL → BI → UB	0.068	0.014	0.031	0.087	4.953	<0.001
SDT → BI → UB	0.270	0.027	0.163	0.271	10.156	<0.001

LLCI = lower-level confidence interval; ULCI = upper-level confidence interval. Bootstrapped LLCI and ULCI represent the lower and upper limits of the 95% confidence interval obtained using percentile bootstrapping

BI. Additionally, PI showed a substantial indirect effect (effect = 0.096, z = 6.004, p < 0.001), highlighting individual innovativeness as a crucial determinant of actual GAI adoption through increased intention. TV had a particularly robust indirect effect on UB (effect = 0.131, z = 5.056, p < 0.001), suggesting that lecturers' acknowledgement of the educational benefits of GAI significantly boosts their intention and adoption. Further, AL positively affected UB through BI (effect = 0.068, z = 4.953, p < 0.001), indicating that higher AI literacy promotes intention and adoption. Last, SDT, as reflected on student intrinsic motivation, displayed the strongest indirect effect on UB (effect = 0.270, z = 10.156, p < 0.001), highlighting that lecturers' psychological needs for autonomy, competence and relatedness critically drive their intention and subsequent behaviour regarding GAI adoption.

4.5 Moderating effects

To investigate the moderating role of motivation through SDT on the relationships among the UTAUT constructs (PE, EE, SI, FC and BI) and extended variables (i.e.,

Table 7 Moderation effects of self-determination theory on behavioural intention

Predictor	Moderator (SDT)	Interaction (Predictor × SDT)	β	t-value	*p*-value
PE	SDT	PE × SDT	0.161	6.091	< 0.001
EE	SDT	EE × SDT	0.148	4.891	< 0.001
SI	SDT	SI × SDT	0.180	7.121	< 0.001
PI	SDT	PI × SDT	0.218	6.867	< 0.001
FC	SDT	FC × SDT	0.216	7.811	< 0.001
TV	SDT	TV × SDT	0.126	4.281	< 0.001
AL	SDT	AL × SDT	0.158	5.519	< 0.001

PI, AL and TV), moderation analysis was conducted. Table 7 summarises the findings. The results demonstrate that the inclusion of SDT as a moderator significantly enhanced the explanatory power of the model. Specifically, SDT positively and significantly moderated the relationships between PE (ß=0.161, t = 6.091, $p < 0.001$), EE (ß=0.148, t = 4.891, $p < 0.001$), SI (ß=0.180, t = 7.121, $p < 0.001$), PI (ß=0.218, t = 6.867, $p < 0.001$), FC (ß=0.216, t = 7.811, $p < 0.001$), TV (ß=0.126, t = 4.281, $p < 0.001$) and AL (ß=0.158, t = 5.519, $p < 0.001$) and BI. These findings indicate that lecturers with higher intrinsic motivation and psychological needs (SDT) tend to exhibit stronger intentions to use GAI tools when influenced by performance expectations, ease of use, social influence, individual innovativeness, facilitating support, perceived educational values, and AI literacy. The moderating effects of SDT thus underscore the critical role of autonomy and motivation in shaping lecturers' behavioural intention towards adopting GAI technologies.

5 Discussion

5.1 Overview of the results

The study examined the determinants of lecturers' readiness to adopt GAI, extending the UTAUT framework with SDT and individual factors (PI, TV, AL). Given the cross-sectional design, the SEM estimates are interpreted as predictive relationships. Structural modelling indicated that most hypothesised relationships were statistically supported. Consistent with prior research (Venkatesh et al., 2003; Budhathoki et al., 2024), PE, EE, SI, and FC were significant predictors of behavioural intention (BI). However, the relative salience differed. FC and SI showed comparatively stronger associations than is often reported in student-focused studies (e.g., Strzelecki, 2024; Habibi et al., 2023), which aligns with the view that lecturers' adoption is more contingent on institutional support and peer expectations (Marks & Thomas, 2022; Rahiman & Kodikal, 2024). Among the extended variables, TV showed the strongest association with BI, followed by PI and AL. This underscores that lecturers' willingness to adopt GAI is anchored in perceived pedagogical benefit rather than technological novelty (Sitar-Taut and Mican 2021; Wang et al. 2025a, 2025b). PI reflected openness to experimentation, while AL reduced uncertainty and strengthened confidence, potentially translating into inclination to adopt GAI for educational purposes (Wang et al. 2023a, 2025b). Taken together, these findings indicate that adoption readiness is associated with both perceived pedagogical relevance and competence-related preparedness to innovate.

SDT-related need fulfilment showed the strongest links to BI. It was also positively related to adoption behaviour (UB) and exhibited moderation effects on selected UTAUT pathways. For example, interactions between SDT and expectancy constructs (PE, EE) revealed that higher intrinsic motivation amplified the effect of performance and effort beliefs on BI (Bergdahl et al., 2023; Hsu, 2023; Ryan & Deci, 2020; Zheng et al., 2024). This pattern is consistent with the interpretation that motivational conditions can shape how cognitive appraisals translate into intention, extending UTAUT with a motivational perspective. Finally, BI was the strongest direct predictor of actual adoption (UB), consistent with UTAUT's intention and behaviour logic. UB was also directly associated with FC and SDT, suggesting that both structural support and psychological need fulfilment relate to use beyond intention alone. Mediation analysis further confirmed that BI transmitted the effects of multiple antecedents, with SDT showing the strongest indirect association with UB via BI. Overall, the results emphasise SDT as a key correlate of lecturers' preparedness, operating through both direct and indirect pathways in the proposed model.

5.2 Theoretical and practical contributions

The study offers important theoretical and practical contributions on GAI adoption in education from lecturers' perspectives. Theoretically, the integration of SDT with UTAUT provides a framework that extends expectancy-based explanations by incorporating motivational internationalisation processes. SDT-related need fulfilment emerged as the strongest predictor of BI while significantly moderating selected UTAUT relationship, suggesting that novel technology readiness among lecturers may be shaped not only by perceived utility and ease, but also by whether adoption is experienced as agentic, manageable, and socially supported. In this regard, the findings align with Zheng et al.'s (2024) study in highlighting the importance of intrinsic motivational dynamics in lecturers' readiness to engage with GAI. More importantly, this integrated approach suggests that adoption models may benefit from incorporating motivational conditions when explaining variance in professional technology acceptance, particularly where sustained pedagogical change is needed. A second contribution concerns the salience of teaching values. TV showed a relatively strong association with BI, supporting that lecturers' intentions may depend on values-based judgements about pedagogical legitimacy and utility, not simply generic usefulness. TV captures perceptions of pedagogical affordances (e.g., personalised feedback generation, adaptive content creation, and assessment design support). This finding echoes Ain et al. (2016) and Foroughi et al. (2024) that perceived educational values of GAI is closely linked to lecturers' willingness to engage with GAI in routine teaching practice. The implication is that this domain-specific conceptualisation provides theoretical precision for understanding professional technology adoption where context- and discipline-specific values supersede general usefulness. Finally, AI literacy showed a more modest direct link to BI, yet it remains theoretically important as a capability resource that may underpin ethical and confident adoption. While AI literacy has been conceptualised, empirical evidence linking lecturers' AI literacy to overall readiness for GAI remains limited (Mah & Groß, 2024; Schmidt et al., 2025). Our findings suggest that AI literacy may function as a facilitative condition in technology-enhanced education contexts, potentially shaping whether perceived values and motivational conditions can be translated into sustained adoption. That is, without basic literacy, even strong motivation and perceived values may not lead to adoption, suggesting that AL should be conceptualised as core factor that influences technology readiness.

Regarding the practical implications, institutional strategies to support GAI-integrated teaching may be more effective when they go beyond technical training alone. Given SDT's direct and moderating associations, professional development may benefit from incoporating autonomy-supported elements (e.g., providing choices and rationale, enabling self-paced experimentation), competence support (e.g., scaffolded progression from basic operational skills to pedagogically grounded applications), and relatedness support (e.g., discipline-specific communities of practice, peer mentoring, and teaching practice demonstration). Such approaches may help transform one-off workshops into more sustained developmental ecosystems aligned with lecturers' motivational conditions. In addition, the salience of teaching values indicates that institutional communication may be more persuasive when it foregrounds pedagogical impact rather than tool features. Universities could document and disseminate evidence-based examples of teaching improvement (e.g., efficiencies in feedback processes, enhanced learning design), and support lecturers to integrate GAI within exisitng curriculum and assessment development practices. Developing discipline-specific use cases may help align GAI adoption with lecturers' pedagogical philosophies and professional standards, thereby strengthening value-based legitimacy. Additionally, with respect to AI literacy, universities may consider implementing more systematic competence-building provision rather than relying on ad hoc training. This could include practical skill development (e.g., promoting strategies, output evaluation), ethical and governance dimensions (e.g., integrity, privacy, bias awareness), and guidance on appropriate use and limitations. Embedding these components within continuing professional development frameworks may support sustained capability as GAI technologies evolves. Finally, facilitating conditions remained important for both intention and actual adoption, indicating that institutional infrastructure and governance are closely related to full embrace of GAI in institutional education. Beyond technical provisions, universities may consider developing coordinated support structures, including accessible expertise for pedagogically contextualised assistance, clear policy guidance, and visible leadership endorsement through resource allocation and workload recognition. Such support may help position GAI adoption as a collectively enabled and pedagogically validated practice rather than solely an individual initiative.

5.3 Hypotheses testing outcomes

The study tested the proposed hypotheses concerning the determinants of lecturers' readiness to adopt GAI. The results are summarised as follows:

- H1a–d (UTAUT constructs): Performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) were all found to significantly predict behavioural intention (BI) ($\beta = 0.076$, $p = 0.020$; $\beta = 0.115$, $p = 0.004$; $\beta = 0.108$, $p = 0.043$; $\beta = 0.160$, $p < 0.001$). Thus, H1a–d were supported.
- H2a–c (Individual attributes): Teaching values (TV), personal innovativeness (PI), and AI literacy (AL) had significant positive effects on BI ($\beta = 0.318$, $p < 0.001$; $\beta = 0.194$, $p < 0.001$; $\beta = 0.088$, $p = 0.011$), supporting H2a–c.
- H3 (SDT → BI): Self-determination theory (SDT) factors strongly predicted BI ($\beta = 0.339$, $p < 0.001$), confirming H3.
- H4 (BI → UB): BI significantly predicted use behaviour (UB) ($\beta = 0.457$, $p < 0.001$), supporting H4.
- H5a–b (Direct effects on UB): Facilitating conditions and SDT directly predicted UB ($\beta = 0.154$, $p = 0.022$; $\beta = 0.235$, $p < 0.001$), supporting H5a–b.
- H6 (Mediation): Mediation analysis confirmed that BI significantly mediated the relationships between all antecedents (PE, EE, SI, FC, TV, PI, AL, SDT) and UB.
- H7 (Moderation): Moderation analysis revealed that SDT significantly moderated and amplified the effects of PE, EE, SI, PI, FC, TV, and AL on BI, supporting H7.

In summary, all proposed hypotheses were supported by the empirical findings, with SDT emerging as both the strongest direct determinant of BI and the most influential moderator.

6 Conclusion

This study examined how university lecturers' motivational needs, cognitive appraisals, and individual attributes influence readiness for GAI use in HE. We surveyed 651 lecturers from Chinese universities and our findings showed that technology use is a motivated behaviour rather than purely a rational calculation. Our discussion above addresses the formed research questions, in doing so identifying that UTAUT constructs (PE, EE, SI, FC) predicted behavioural intention (BI) and adoption, but SDT emerged as the strongest predictor and moderator, underscoring the role of *autonomy*, *competence*, and *relatedness* in shaping technology acceptance. Individual-level determinants (teaching value, AI literacy, personal innovativeness) proved crucial, suggesting context-specific pedagogical considerations outweigh generic technology perceptions. Yet, despite offering useful insight, limitations can be identified within the study.

6.1 Limitations

Despite the study's breadth and our focus on ethical design, several methodological limitations should be acknowledged, and are discussed further in the concluding remarks. First, the reliance on a cross-sectional online survey may introduce common method bias and restrict causal inference; after all, measures were self-reported and collected at a single point in time. Second, while the sample of 651 lecturers across mainland China provided broad representation, the use of convenience sampling limits generalisability, particularly as the number and distribution of universities engaged was not precisely quantified. Third, although validated instruments were employed, responses may have been shaped by social desirability bias or by participants' varying levels of familiarity with GAI at the time of data collection. Finally, the exclusive use of quantitative measures means the study may not fully capture the nuanced, contextualised experiences underlying lecturers' motivational orientations and readiness for GAI integration, and hence a mixed-methods qualitative follow up is advised, with a complementary longitudinal focus for future research.

6.2 Recommendations

Pragmatically, institutions should build ecosystems that support psychological needs, demonstrate pedagogical value, and strengthen AI literacy, rather than focusing solely on financial or technical provision. Based on our findings, we can offer the following recommendations to policy makers and leaders:

1. Embed psychological needs in HE lecturers professional development: Training should nurture lecturers' autonomy, competence, and relatedness, since we found SDT was the strongest predictor of behavioural intention ($\beta = 0.339$, $p < 0.001$) and also directly influenced actual use (UB) ($\beta = 0.235$, $p < 0.001$).
2. Highlight pedagogical value, not just technical features in such development: Demonstrating GAI's teaching value (TV) is essential, as we found it was the largest individual determinant of intention ($\beta = 0.318$, $p < 0.001$). Communicating pedagogical benefits will thus encourage adoption beyond technical novelty.

3. Strengthen AI literacy systematically across institutions: AI literacy (AL), we found, had a significant effect on intention ($\beta = 0.088$, $p = 0.011$) and an indirect effect on use through BI. Universities should implement structured literacy programmes addressing awareness, usage, evaluation, and ethics.
4. Provide robust institutional support: Facilitating conditions (FC) significantly predicted intention we found, ($\beta = 0.160$, $p < 0.001$) and directly predicted use ($\beta = 0.154$, $p = 0.022$). Universities must ensure infrastructure, policies, and technical assistance are in place.
5. Foster innovation through safe experimentation and communities of practice: Personal innovativeness (PI) influenced intention ($\beta = 0.194$, $p < 0.001$) in our study, thus indirectly affected use. Institutions should provide opportunities for safe experimentation, such as pilots and sandbox projects.
6. Leverage peer and social influence: Social influence (SI) positively predicted intention ($\beta = 0.108$, $p = 0.043$) in our study. Universities can thus amplify adoption by cultivating peer networks, mentoring, and showcasing departmental success stories.
7. Integrate adoption into long-term professional ecosystems: Since behavioural intention strongly predicted actual use in our findings ($\beta = 0.457$, $p < 0.001$), adoption strategies should be sustained through ongoing CPD frameworks, not one-off workshops, to translate intention into lasting classroom practices.
8. Address cultural and contextual factors: Our moderation analysis showed that SDT strengthened the impact of all predictors (e.g., PE × SDT, $\beta = 0.161$, $p < 0.001$). Universities should tailor training and support to disciplinary and cultural contexts, as motivation shapes the strength of other determinants.

To translate the empirical findings into actionable guidance, Table 8, noted below, summarises the key determinants of lecturers' AI adoption and their implications for institutional strategy alongside evolving teaching practice within universities, thereby providing structured direction for policy makers:

6.3 Future directions

Consequently, the adoption strategies describe above offer a direction forward for universities, which demonstrates that it is important leaders integrate and build a culture of continuous AI professional development that fosters autonomy, agency and confidence amongst faculty. The findings described set a foundation for future research, which should examine how these dynamics vary across cultural and disciplinary contexts, and distinguish externally imposed from intrinsically developed motivation.

Table 8 Summary of recommendations

Key empirical finding	Theoretical basis	Practical recommendation for universities
Psychological need fulfilment (SDT) was the strongest predictor of behavioural intention and directly influenced GAI use.	Self-Determination Theory (autonomy, competence, relatedness).	Design professional development training and invest suitably therein to support lecturer autonomy (choice and agency), competence (scaffolded skill development), and relatedness (peer mentoring and communities of practice) rather than mandating GAI use.
Behavioural intention strongly predicted actual GAI use.	UTAUT (intention–behaviour pathway).	Move beyond awareness and prohibition campaigns by embedding GAI engagement within sustained professional development and workload-recognised teaching innovation initiatives, alongside ties to curriculum shape and graduate destinations focusing.
Teaching values showed the largest individual effect on behavioural intention.	Pedagogical identity and values-based adoption.	Frame GAI adoption around pedagogical benefits and academic integrity, using discipline-specific teaching cases that align AI use with established educational values, re-examining how to assess and mark student-adopted integrated AI practice.
AI literacy positively influenced intention and indirectly influenced use.	Capability resources and responsible AI use.	Implement structured AI literacy programmes that address operational skills, critical evaluation of outputs, and ethical considerations such as bias, privacy, and assessment fairness.
Facilitating conditions directly influenced both intention and actual use.	Organisational support and infrastructure.	Provide reliable technical infrastructure, clear institutional policies, and accessible pedagogical support services to legitimise and sustain GAI integration.
Personal innovativeness predicted behavioural intention.	Openness to innovation.	Encourage safe experimentation through pilot projects, innovation grants, and sandbox environments that reduce perceived risk of adopting GAI in teaching.
Social influence positively affected intention.	Professional norms and peer effects.	Leverage peer influence by showcasing effective practice, supporting departmental champions, and fostering collegial dialogue around GAI use.

Appendix

Table 9 Item analysis and internal consistency reliability

Item	Corrected Item-Total Correlation (CITC)	Cronbach's α if Item Deleted	Cronbach's α
SDT1	0.819	0.947	0.952
SDT2	0.690	0.949	
SDT3	0.685	0.949	
SDT4	0.655	0.950	
SDT5	0.670	0.950	
SDT6	0.747	0.948	
SDT7	0.773	0.947	
SDT8	0.748	0.948	
SDT9	0.733	0.948	
SDT10	0.663	0.950	
SDT11	0.779	0.947	
SDT12	0.763	0.948	
SDT13	0.746	0.948	
SDT14	0.805	0.947	
SDT15	0.762	0.948	
PE16	0.821	0.806	0.876
PE17	0.723	0.844	
PE18	0.676	0.863	
PE19	0.717	0.847	
EE20	0.754	0.825	0.872
EE21	0.695	0.850	
EE22	0.719	0.838	
EE23	0.740	0.830	
SI24	0.629	0.761	0.807
SI25	0.651	0.739	
SI26	0.684	0.704	
FC27	0.725	0.790	0.848
FC28	0.672	0.822	
FC29	0.691	0.807	
FC30	0.690	0.808	
PI31	0.633	0.802	0.824
PI32	0.741	0.691	
PI33	0.666	0.769	
TV34	0.634	0.834	0.851
TV35	0.698	0.807	
TV36	0.756	0.784	
TV37	0.678	0.815	
AL38	0.818	0.908	0.924
AL39	0.763	0.913	
AL40	0.716	0.916	
AL41	0.735	0.915	
AL42	0.694	0.918	
AL43	0.749	0.914	
AL44	0.746	0.914	
AL45	0.727	0.915	

Table 9 (continued)

Item	Corrected Item-Total Correlation (CITC)	Cronbach's α if Item Deleted	Cronbach's α
BI46	0.662	0.812	0.837
BI47	0.746	0.730	
BI48	0.693	0.781	
UB49	0.736	0.812	0.863
UB50	0.746	0.805	
UB51	0.742	0.808	

Table 10 Goodness-of-fit indices for the overall measurement model

Index	χ^2/df	GFI	AGFI	NFI	TLI	CFI	RMSEA
Overall Model	1.679	0.904	0.892	0.913	0.960	0.963	0.032
Recommended Value	<3	>0.8	>0.8	>0.9	>0.9	>0.9	<0.08
Criteria met	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 11 Descriptive statistics for the research variables

Variable	Min	Max	Mean	SD	Median
PE	1.00	5.00	3.70	1.03	4.00
EE	1.00	5.00	3.73	0.91	4.00
SI	1.00	5.00	3.65	1.06	3.67
PI	1.00	5.00	3.63	0.85	3.67
FC	1.00	5.00	3.80	0.92	4.00
TV	1.00	5.00	3.95	0.87	4.00
AL	1.13	5.00	3.60	0.93	3.63
SDT	1.00	4.87	3.48	0.83	3.67
BI	1.00	5.00	3.99	0.92	4.33
UB	1.00	5.00	3.61	1.03	4.00

Table 12 Collinearity diagnostics

Variable	Tolerance	Variance Inflation Factor (VIF)
Performance Expectancy (PE)	0.428	2.336
Effort Expectancy (EE)	0.435	2.299
Social Influence (SI)	0.387	2.584
Personal Innovativeness (PI)	0.412	2.427
Facilitating Conditions (FC)	0.376	2.659
GAI Teaching Values (TV)	0.369	2.710
AI Literacy (AL)	0.398	2.513
Self-Determination Theory (SDT)	0.785	1.274
Behavioural Intention (BI)	0.324	3.086

VIF values below 10 and Tolerance values above 0.1 indicate no serious multicollinearity concerns

Table 13 Correlation coefficients among the study variables

Variables	UB	PE	EE	SI	PI	FC	TV	AL	BI	SDT
UB	1									
PE	0.348***	1								
EE	0.296***	0.463***	1							
SI	0.341***	0.501***	0.502***	1						
PI	0.282***	0.489***	0.445***	0.577***	1					
FC	0.436***	0.574***	0.532***	0.487***	0.446***	1				
TV	0.366***	0.552***	0.509***	0.581***	0.529***	0.530***	1			
AL	0.382***	0.532***	0.509***	0.571***	0.516***	0.534***	0.513***	1		
BI	0.571***	0.606***	0.588***	0.615***	0.585***	0.618***	0.645***	0.597***	1	
SDT	0.402***	0.206***	0.186***	0.179***	0.131***	0.213***	0.137***	0.193***	0.445***	1

Table 14 Goodness-of-fit indices for the structural equation model

Fit index	Obtained value	Recommended threshold	Criteria Met
Chi-square/degrees of freedom (χ^2/df)	1.694	< 3	Yes
Goodness-of-Fit Index (GFI)	0.903	> 0.80	Yes
Adjusted Goodness-of-Fit Index (AGFI)	0.891	> 0.80	Yes
Normed Fit Index (NFI)	0.911	> 0.90	Yes
Tucker-Lewis Index (TLI)	0.959	> 0.90	Yes
Comparative Fit Index (CFI)	0.962	> 0.90	Yes
Root Mean Square Error of Approximation (RMSEA)	0.032	< 0.08	Yes

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Author contributions Per CRediT: YL was responsible for research data protocols, data analysis and modelling. MJD was responsible for the literature review, supporting data analysis and discussion. Both contributed equally to the conceptualisation of the manuscript. The authors declare no competing interests, and per COPE, identify AI tools were used for copy-editing and language proofing purposes.

Data Availability Correspondence and requests for materials and data availability should be addressed to both authors and will be considered on appropriate request.

Declarations

Ethical approval This study received ethical approval from the Institutional Review Board under project with IRB ID ER-LRR-11000128120240606102842 at the affiliated university of YL. All procedures performed in this study adhered to the ethical standards outlined in the Declaration of Helsinki. Participants' confidentiality and anonymity were strictly maintained to protect their privacy throughout the research process.

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Authors and Affiliations

Yujuan Luo[1] · Michael James Day[2]

✉ Michael James Day
m.j.day@greenwich.ac.uk

Yujuan Luo
yujuan.luo@nwpu.edu.cn

1 Northwestern Polytechnical University, Xi'an, China

2 University of Greenwich, London, UK