Australasian Journal of Educational Technology, 2026, 42(3).

GenAI as a frenemy in teaching: Perceived autonomy and risks

Hai Min Dai
Shanghai Jiao Tong University, China
https://orcid.org/0000-0002-0015-8727

Kaige Ni
miHoYo Co., Ltd, China
https://orcid.org/0000-0003-1177-4725

Han Meng
Shanghai Jiao Tong University, China
https://orcid.org/0009-0005-9633-9547

Bei Ju
University of Manchester, United Kingdom
https://orcid.org/0000-0001-8324-9001

Joseph Crawford
University of Tasmania, Australia
https://orcid.org/0000-0002-2191-6216

Timothy Teo
The Chinese University of Hong Kong, China
https://orcid.org/0000-0002-7552-8497

Generative artificial intelligence (GenAI) has the potential to transform education, yet little is known about how teachers' perceptions of its autonomy and their risk aversion influence their willingness to adopt. This mixed methods study utilised a human-AI interaction lens to investigate the psychological processes shaping varied adoption. Survey data from 287 teachers across 27 countries and regions were analysed using structural equation modelling with bootstrapped mediation tests, complemented by thematic analysis. Research results revealed that integrating GenAI in teaching is neither straightforward nor effortless. Teachers largely viewed it as semi-autonomous, preferring to retain full control over their teaching. Their awareness of situational factors may contribute to the perception of GenAI as semi-autonomous and weaken the link between artificial autonomy and their adoption intention. As the appeal of automation diminished, concerns about potential harm grew, with risk aversion playing a significant role in adoption decisions. Teachers were more concerned about students' use of GenAI than their own. Overall, GenAI adoption requires careful consideration of context and human-AI interaction. This study enhances understanding of these dynamics, highlighting the psychological processes influencing adoption and offering insights for AI policy and professional training aimed at fostering thoughtful integration into education.

Implications for practice or policy:

- Instructional designers could improve adoption by sharing discipline-specific examples aligned with instructional needs.
- Institutions could tailor training to teachers' GenAI use experience, with novices introduced to pedagogical potential and experienced teachers supported with practical strategies.
- Institutions could fund AI literacy initiatives, integrating AI ethics into curricula and adapting assessments for ethical and effective AI use.
- Policymakers should develop clear guidelines and risk management strategies to address integrity and student misuse.

Keywords: artificial autonomy, human-AI interaction, GenAI adoption, risk aversion, mixed method

Introduction

Generative artificial intelligence (GenAI) has elicited mixed reactions among educators. Some see it as transformative for enhancing teaching and learning by boosting engagement, facilitating asynchronous communication and overcoming access barriers in distance learning (Firat, 2023; Giannakos et al., 2025; OECD, 2026). Research reported its application across disciplines and teaching contexts (Webb & Galamba, 2026; Wong et al., 2024). Despite these benefits, some teachers hesitate to integrate GenAI into their teaching routines (Xue et al., 2026; Zhou et al., 2024). Their concerns include challenges to academic integrity, the risk of hindering students' deep learning (Adeshola & Adepoju, 2023; Jose et al., 2025), disruption of traditional teaching methods and potential threat to inclusivity and diversity in education (Cotton et al., 2024; Giannakos et al., 2025; Yang, 2023). These issues place pressure on institutions to redesign courses and assessments, often requiring substantial resources (An et al., 2025; Tran et al., 2025) and raising broader questions about the appropriate role of AI in education. Additionally, educators worry about inadequate training and support, and even the possibility of job displacement. However, drawing on lessons from past disruptive technologies, the resistance to innovations could lead to counterproductive outcomes (Eager & Brunton, 2023). Teachers' reluctance to embrace AI tools may push students to utilise them covertly, thereby undermining trust and academic integrity. Additionally, such resistance can stifle educational innovation and hinder the development of AI-related critical thinking skills (Zawacki-Richter & Jung, 2023), leaving students unprepared for an AI-ubiquitous job market. Thus, teachers' adoption is particularly relevant given the increasing acceptance of AI tools among younger generations (Lyu et al., 2025; Šedlbauer et al., 2024).

Unlike traditional educational technologies, GenAI represents a leap in simulating human intelligence. When evaluating its instructional use, teachers may anthropomorphise it, attributing autonomy and engaging with it accordingly (T. Jiang et al., 2024). These psychological processes involve assessing the extent to which GenAI can or should function without human intervention (artificial autonomy) and their personal tolerance for uncertainties (risk aversion) when delegating teaching tasks to GenAI. By balancing both technical and personal factors, educators determine its usefulness, ease of use, their attitude and willingness to incorporate it into their teaching practices. However, artificial autonomy has been under-studied in AI education research, likely because earlier AI tools lacked the sophistication to be seen as autonomous agents. This study addresses this gap by proposing a conceptual model based on the technology acceptance model (TAM; Davis, 1989), integrating artificial autonomy and risk aversion. This mixed method study aimed to answer the following research questions (RQs):

- RQ1. To what extent can the proposed conceptual model explain teachers' adoption of GenAI in teaching?
- RQ2. Is artificial autonomy a significant determinant in explaining teachers' adoption of GenAI in teaching?
- RQ3. Is risk aversion a significant determinant in explaining teachers' adoption of GenAI in teaching?

The findings from this study will illuminate how teachers perceive human-AI interaction and how this perception might shape their responses towards GenAI. These insights will encourage teachers to thoughtfully integrate GenAI in education, empowering institutions to adeptly navigate the array of opportunities and challenges presented by GenAI.

Literature review

The following section will review the studies on teachers' adoption of GenAI, perceptions of GenAI's autonomy and risk aversion respectively.

Teachers' adoption of GenAI in education

Recent studies have suggested that teachers' acceptance of GenAI remains mixed. While some report positive attitudes towards its potential for lesson planning, content generation and student engagement (Kim et al., 2025; Lee et al., 2024), other works have suggested that teachers' adoption decisions remain conditional and responsive to contextual considerations (Miranda & Chamorro-Mera, 2026). Understanding the factors contributing to the variations in teachers' acceptance of GenAI can inform interventions and professional programmes that support its meaningful integration into teaching. To date, models and theories have been proposed to elucidate technology acceptance and use (King & He, 2006), with TAM being the most influential one (Granić, 2023). TAM highlights perceived usefulness (PU) and perceived ease of use (PEU) as central to adoption (Davis et al., 1989). PU is conceptualised as the degree to which an individual believes that using a particular technology would enhance performance, while PEU refers to the extent to which it is perceived as effortless (Davis, 1989). These two constructs have been reported to significantly influence educators' attitudes and intentions (Al Darayseh, 2023). Within TAM, behavioural intention (BI), a determinant of actual use, is shaped by both individuals' attitudes towards technology use (ATT) and PU, with ATT itself being influenced by PU and PEU (see Figure 1).

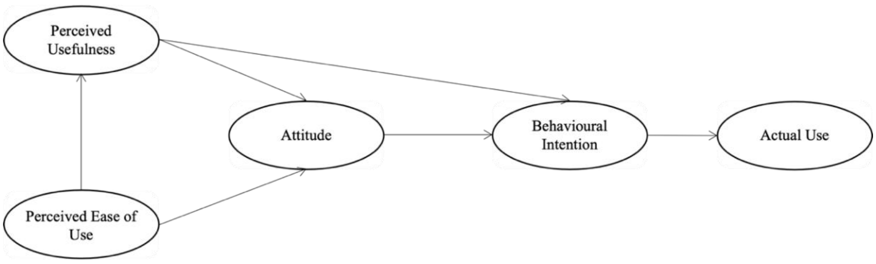

Figure 1. TAM

Meta-analyses of studies utilising TAM as a theoretical framework to explain teachers' adoption of technologies (Scherer et al., 2019; Scherer & Teo, 2019) have consistently underscored its robust predictive capability. Likewise, the present study posited that TAM could be applicable in explaining teachers' willingness to adopt GenAI in teaching. Thus, we adopted TAM as the baseline model and hypothesised that:

- H1. PU is significantly associated with ATT.
- H2. PU is significantly associated with BI.
- H3. PEU is significantly associated with PU.
- H4. PEU is significantly associated with ATT.
- H5. ATT is significantly associated with BI.

TAM has continuously evolved to adapt to diverse technological contexts and populations (Marangunić & Granić, 2015). This study extends TAM to integrate teachers' perceptions of GenAI's autonomy and the risk aversion, ensuring that the conceptual model aligns with the characteristics of GenAI and the specific research context.

GenAI's autonomy in education

AI is designed with human-like features and exhibits a form of agency (Boulus-Rødje et al., 2024). GenAI, in particular, learns from user input and generates content tailored to individual preferences and needs. This agentic feature might lead users to anthropomorphise GenAI, attributing human-like traits to it, which can, in turn, shape their subsequent behaviours (Hu et al., 2021; Uysal et al., 2023). Perceptions of GenAI as autonomous have important implications for its adoption across domains.

GenAI has been ascribed diverse anthropomorphised roles by educational institutions and academics in the literature. Some teachers may see GenAI as a competitor, fearing that it could diminish or supplant their roles, particularly where AI is framed in terms of automation or the replacement of human work (Raisch & Krakowski, 2021). On the flip side, some have emphasised the optimistic possibilities of AI in assisting or augmenting learning and teaching (Molenaar, 2022), viewing GenAI as helper, partner or collaborator. They have advocated that human-AI partnership, by leveraging human strengths – such as domain expertise, situational awareness, creative thinking and ethical judgement – with AI's computational powers and analytical capabilities, can foster more effective learning than working alone (Frey & Osborne, 2017; Holstein & Aleven, 2022; T. Jiang et al., 2024).

Instead of assigning discrete roles for AI in human-AI interaction, researchers have argued that AI's role in education could be seen as a continuum, reflecting the varying degree to which AI is decoupled from human involvement (Cukurova et al., 2019; Jose et al., 2025; OECD, 2026). This perspective aligns closely with the concept of artificial autonomy from the research field of human-computer and human-robotics interaction. Artificial autonomy can be understood from engineering or user perspectives. In this study, we focused on perceived artificial autonomy from a user perspective, defining it as the extent to which teachers perceive GenAI as capable of independently carrying out assigned instructional tasks with limited human intervention (Beer et al., 2014; Hu et al., 2021). This user-facing understanding of autonomy is particularly relevant in educational contexts where agentic AI systems are increasingly discussed in terms of pedagogical roles and autonomy levels (Kostopoulos et al., 2025).

Research on automation and human-robot interaction has introduced various taxonomies to describe the continuum of artificial autonomy. These include frameworks such as Sheridan and Verplank's (1978) level of decision-making automation, Endsley and Kaber's (1999) levels of automation, Parasuraman et al.'s (2000) conceptual model for automation types and level of automation and Beer et al.'s (2014) synthesised framework of robot autonomy in human-robot interaction. Horvers and Molenaar (2022, as cited in Molenaar, 2022) introduced a six-level automation model (see Figure 2) to capture teachers' perceptions regarding AI's autonomy, providing a relevant framework for understanding AI integration in educational settings. The model illustrates that the level of automation ascends from left to right, starting with AI offering support to teachers in specific tasks and culminating in complete automation where AI independently oversees educational processes. It is worth noting that though the model categorises artificial autonomy into six levels, these should be understood as a continuum with unspecified intermediate levels rather than strictly discrete categories.

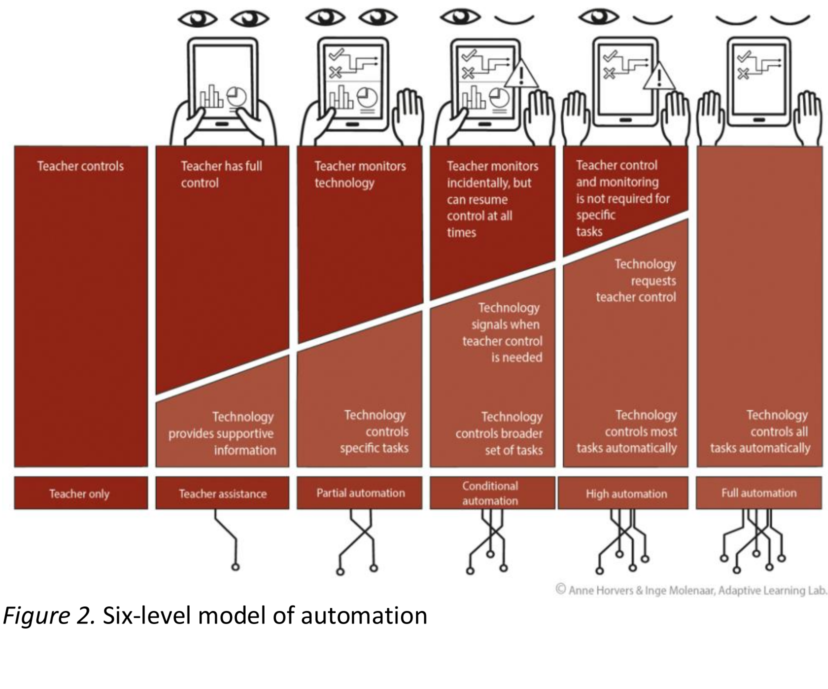

Figure 2. Six-level model of automation

Note. The chart illustrates that higher artificial autonomy correlates with more data sources (dots at the bottom). The eyes at the top symbolise teacher supervision and the hands represent teacher control over teaching arrangements (Horvers & Molenaar, 2022, as cited in Molenaar, 2022).

Teachers' perceptions of GenAI's autonomy – ranging from assistive to fully automated – significantly shape teachers' acceptance of emerging AI technologies (Molenaar, 2022). Those who advocate for complete teacher control (Level One: Teacher Only) tend to perceive GenAI as minimally beneficial for teaching (low PU), hold unfavourable attitudes (low ATT) and, in turn, may resist GenAI (low intention). Conversely, teachers who recognise greater GenAI autonomy are more likely to see its utility and develop more positive attitudes, leading to stronger intentions to use it in teaching. Therefore, we proposed that:

- H6. AA is significantly associated with PU.
- H7. AA is significantly associated with ATT.
- H8. AA is significantly associated with BI.
- H9. PU mediates the relationship between AA and BI.
- H10. ATT mediates the relationship between AA and BI.

Risk aversion

Educators worry that integrating GenAI into education could lead to academic dishonesty (Y. Jiang et al., 2024) and students' overreliance on AI (Zhang & Xu, 2025), hindering the development of their creative and critical thinking skills (Darvishi et al., 2024). Additional worries include the reliability of the AI-generated content and the unknown ethical challenges associated with its usage. While these concerns are widely acknowledged, individuals perceive them as risks to varying degrees. This variation in risk perception may stem from a personal trait: risk aversion.

Risk aversion (RA) denotes individuals' inclination to favour certainty and minimise risks in decision-making situations, even when the riskier option offers an equal or even greater expected value (Fox et al., 2015; Lilleholt, 2019; Pratt, 1978). Prior studies have underscored the pivotal role of risk aversion in shaping teachers' acceptance of technologies in educational settings, ranging from digital technologies in classrooms to online learning platforms (Bøe et al., 2015; Henderson & Corry, 2021; Howard, 2011, 2013; Howard & Mozejko, 2015). Howard's mixed methods studies (2011, 2013) in both Australia and the United States of America indicated that teachers with a lower tolerance for technology-related risks were likely to underestimate the benefits of technology in education (decreased PU). This scepticism could further translate into a negative attitude towards technology usage, diminishing their motivation to incorporate technology into teaching (reduced BI). Bøe et al.'s study on teachers' use of information and communications technology demonstrated that risk aversion had a direct impact on PU. Building on these studies, we integrated risk aversion into the conceptual model as a key factor shaping PU, ATT and BI in GenAI adoption for education:

- H11. RA is significantly associated with PU.
- H12. RA is significantly associated with ATT.
- H13. RA is significantly associated with BI.

Overall, we proposed a conceptual model (illustrated in Figure 3) to elucidate the psychological processes influencing teachers' willingness to adopt GenAI for instructional purposes.

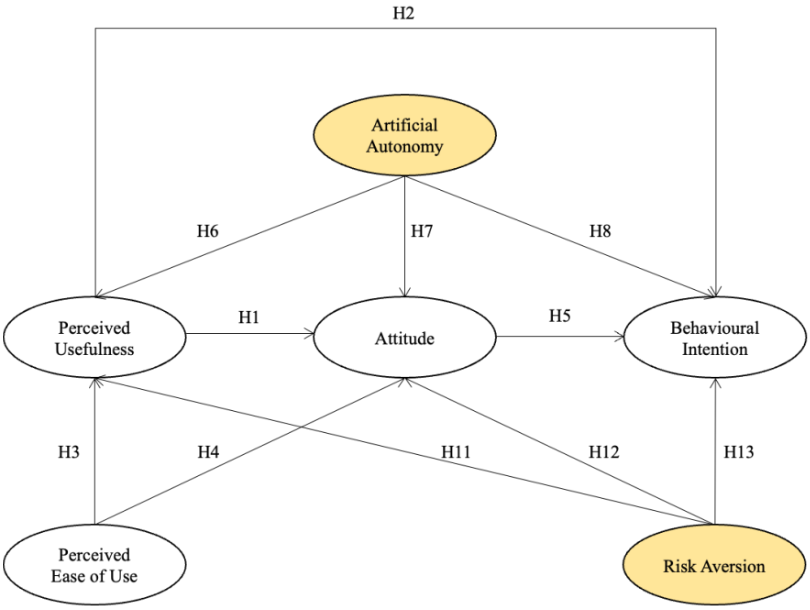

Figure 3. The conceptual model

Methods

This mixed methods research collected data via a questionnaire survey. Numerical data were analysed to test hypotheses and validate the conceptual model. Subsequently, qualitative responses to open-ended questions were employed to interpret and extend the quantitative results, facilitating a nuanced understanding of how perceived artificial autonomy and risk aversion influence GenAI adoption in teaching.

Measures

The questionnaire comprises demographic questions, 20 scale items measuring five constructs, a visual scale for perceived artificial autonomy and two sets of open-ended questions. The open-ended questions examined teachers' views on GenAI's role, their concerns about its use in teaching and how these shape their understanding of human-AI interaction and adoption. In the survey, ChatGPT was used as a practical proxy for broader GenAI, providing a concrete and familiar reference point that enhances response clarity.

An illustration of the six-level automation model (see Figure 2) was included, allowing participants to select the level that best reflected their perceptions of GenAI's autonomy in education. Other constructs were measured by adapting established items from prior studies (An et al., 2023; Chatterjee & Bhattacharjee, 2020; Choi et al., 2023; Mandrik & Bao, 2005; Taylor & Todd, 1995; see Appendix A). All items used a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Reported reliability coefficients for these scales ranged from . 720 to . 970 in prior studies. Items were randomised to reduce sequence bias, and two experts in educational technology assessed the questionnaire for face and content validity.

Procedure

Data were collected via Prolific, an online platform providing diverse and global participants and high-quality data responses (Palan & Schitter, 2018), between September 2023 and May 2024. Participants granted their consent by selecting "agree" in the consent form, permitting the use of their anonymised responses. Because the study examined teachers' intentions to use GenAI in teaching, only respondents with prior experience – confirmed in the initial question – were allowed to participate. Each participant received approximately £2.40 as compensation for completing the questionnaire.

Data analysis

A two-step structural equation modelling approach was employed to analyse numerical data using Mplus (version 7). Structural equation modelling is appropriate for estimating multiple interrelated dependence relationships among latent variables with several indicators (Hair et al., 2010). Confirmatory factor analysis tested measurement reliability and validity, followed by path analysis to evaluate the significance and strength of hypothesised structural relationships.

Mediation analysis examined the indirect effects to reveal how independent variables influence dependent variables (Baron & Kenny, 1986). Bootstrap procedures in Mplus were used to estimate the significance of indirect effects, providing robust confidence intervals even with non-normal data (Preacher & Hayes, 2008). Mediation effect was considered significant if the 95% bootstrap confidence interval did not contain zero.

Thematic analysis (Braun & Clarke, 2006) was performed on textual data to provide a rich and complex understanding on artificial autonomy and risk aversion (RQ2 and RQ3). Using NVivo (version 14), data were read and coded for key ideas, relevant codes were selected and emergent themes were reviewed, refined and clearly defined.

Results

Of the initial 319 respondents, 32 were excluded: 6 were not teachers, 16 lacked GenAI experience and 10 provided unengaged responses, indicated by a reverse-coded item (ATT4) and zero response variance (i.e., identical responses across all items). This data screening process left 287 cases for further analysis (see Table 1 for the demographic information).

Table 1
Demographic information

	Grouping	No. of teachers
Experience of using AI for teaching	Yes	225
	No	62
Artificial autonomy	1 (Teacher only)	12
	2 (Teacher assistance)	130
	3 (Partial automation)	94
	4 (Conditional automation)	40
	5 (High automation)	10
	6 (Full automation)	1
Gender	Male	132
	Female	155
Age	20–29	52
	30–39	133
	40–49	66
	50–59	30
	60 and above	6
Location	Europe	147
	North America	76
	Asia	51
	Africa	5
	Oceania	4
	South America	4
Academic title	Assistant professor or lecturer	166
	Associate professor	56
	Professor	36
	Other[a]	29

	Grouping	No. of teachers
Education level	Bachelor's degree	41
	Master's degree	103
	Doctorate	142
	Not reported	1
Discipline[b]	Arts and humanities	69
	Social sciences, journalism and information	70
	Natural sciences, mathematics and statistics	37
	Education	34
	Business, administration and law	27
	Information and communications technology	19
	Engineering, manufacturing and construction	12
	Health and welfare	9
	Other	10

[a]Other job titles include teaching assistant, research fellow, associate dean and research director.
[b]The classification of disciplines is based on the ISCED Fields of Education and Training (UNESCO Institute for Statistics, 2014).

Assessing normality

Univariate normality was confirmed as values of skewness (-1.178 to -.245) and kurtosis (-0.763 to 1.350) were within recommended thresholds (< 3.0 and < 8.0, respectively) (Kline, 2011). However, multivariate normality was not supported, as Mardia's coefficient value (536.169) exceeded the threshold of 440, calculated using p(p + 2), where p represents the number of observed variables (Raykov & Marcoulides, 2008). Therefore, the maximum likelihood robust estimator in Mplus was used as a robust method for non-normal data sets (Wang & Wang, 2019).

Assessing the measurement model

Convergent validity was supported based on three indexes: composite reliability (CR) > .60 (Hair et al., 2010), Cronbach's alpha > .70 and average variance extracted (AVE) > .50 (Fornell & Larcker, 1981) (see Table 2).

Table 2
Convergent validity (n = 287)

Construct	Item	*M*	*SD*	Standardised loading	CR	AVE	Cronbach's alpha
Behavioural intention	BI1	5.604	1.397	.952	.954	.838	.952
	BI2	5.570	1.368	.950			
	BI3	5.191	1.471	.881			
	BI4	5.033	1.475	.875			
Attitude	ATT1	4.993	1.443	.828	.910	.718	.913
	ATT2	4.877	1.425	.806			
	ATT3	5.286	1.381	.883			
	ATT4	4.957	1.336	.871			
Perceived usefulness	PU1	5.047	1.371	.889	.937	.789	.937
	PU2	5.244	1.373	.841			
	PU3	4.815	1.408	.912			
	PU4	5.162	1.414	.910			
Perceived ease of use	PEU1	5.587	1.232	.723	.860	.607	.860
	PEU2	5.226	1.290	.815			
	PEU3	5.373	1.205	.819			
	PEU4	5.004	1.202	.754			
Risk aversion	RA1	4.754	1.347	.721	.793	.566	.788

Construct	Item	*M*	*SD*	Standardised loading	CR	AVE	Cronbach's alpha
	RA2	4.892	1.387	.636			
	RA3	4.392	1.525	.879			

Discriminant validity was assessed by comparing the square roots of AVEs with the inter-construct correlations. As shown in Table 3, five concerning values (bold and underlined) were identified: the square root of AVEs for BI, ATT and PU were lower than the inter-construct correlations between BI and ATT and between ATT and PU.

Table 3
Discriminant validity

Variable	BI	ATT	PU	PEU	RA
BI	**.915**				
ATT	**.929*****	**.847**			
PU	.881***	**.931*****	**.888**		
PEU	.474***	.538***	.493***	**.779**	
RA	-.210**	-.134	-.060	.035	**.752**

Note. All correlations are statistically significant (**p* < .05, ***p* < .01, ****p* < .001), except for RA and ATT, RA and PEU and RA and PU. The diagonal elements in bold are the square roots of AVE and the off-diagonal elements are the inter-construct correlations.

These results indicate insufficient discriminant validity among BI, ATT and PU, with ATT items correlating more strongly with BI and PU than with ATT itself. As BI and PU remained distinct, ATT was removed from the model. After modification, the square roots of AVEs for all constructs exceeded their inter-construct correlations, supporting the discriminant validity of the refined measurement model (see Table 4).

Table 4
Discriminant validity

Variable	BI	PU	PEU	RA
BI	.915			
PU	.879***	.888		
PEU	.473***	.492***	.779	
RA	-.210**	-.059	.035	.752

Note. All correlations are statistically significant (***p* < .01, ****p* < .001), except for RA and PU and RA and PEU. The diagonal elements are the square root of AVE and the off-diagonal elements are the inter-construct correlations.

A common latent factor was introduced to detect potential common method bias. A comparison between the standardised regression weights from the models with and without common latent factor indicated no issue of common method bias (Podsakoff et al., 2003). The refined measurement model achieved an acceptable model fit: χ^2 (84) = 187.563 (p < .001), χ^2/df = 2.233, comparative fit index (CFI) = .962, Tucker–Lewis index (TLI) = .953, root-mean-square error of approximation (RMSEA) = .066 and standardised root-mean-square residual (SRMR) = .036, all exceeded the guidelines by Hair et al. (2010), that is, $\chi^2/df < 5$, CFI > .90; TLI > .90; RMSEA < .08; SRMR < .05.

Refining and assessing the structural model

With ATT removed from the model, the structural model was redefined. A systematic review by Kelly et al. (2023) highlighted that PU and PEU were frequently employed to predict AI acceptance across contexts. Recent studies have supported this, showing PU and PEU as critical factors in educators' adoption of AI tools in education. Choi et al. (2023) surveyed 215 K-12 teachers in South Korea, confirming PU and PEU as determinants of AI tool acceptance. Similarly, Zhang et al. (2023) analysed data from 452 pre-service teachers in Germany, finding PU and PEU significantly linked to their intentions to use AI for teaching. Therefore, we proposed that the PU and PEU are directly associated with teachers' adoption of GenAI for teaching (see Figure 4 for the refined model).

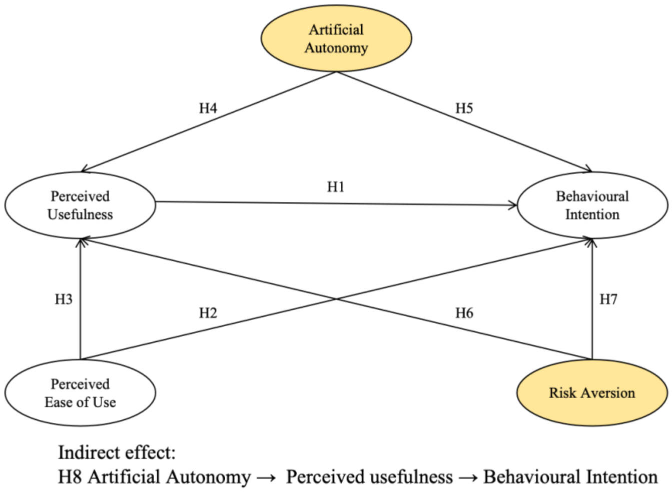

Figure 4. The refined model

The structural model achieved an acceptable model fit: χ^2 (97) = 202.597 (p < .001), χ^2/df = 2.089, CFI = .963, TLI = .954, RMSEA = .062 and SRMR = .041. Five hypothesised relationships were supported but three were not (PEU → BI, AA → BI, RA → PU). The refined model explained 79.8% of the variance in BI. The hypotheses testing results are presented in Table 5 and Figure 5.

Table 5
Hypothesis testing results

No.	Hypothesis	Standardised estimates	Test results
H1	PU → BI	.832***	Supported
H2	PEU → BI	.068	Unsupported
H3	PEU → PU	.479***	Supported
H4	AA → PU	.188***	Supported
H5	AA → BI	.026	Unsupported
H6	RA → PU	-.063	Unsupported
H7	RA → BI	-.163***	Supported
H8	AA → PU → BI	.156***	Supported

****p* < .001.

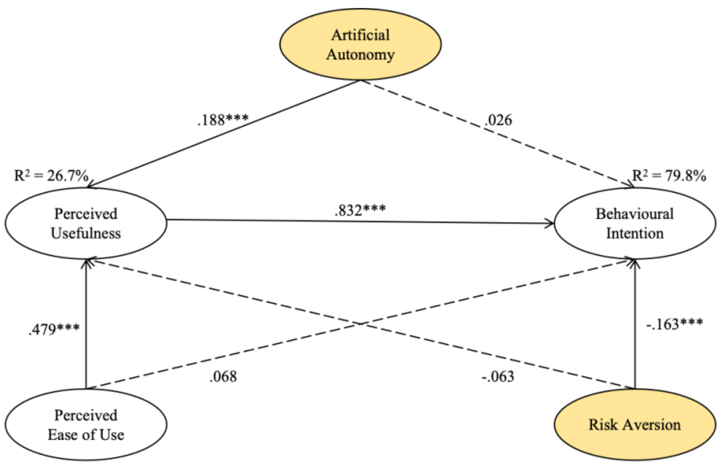

Figure 5. Structural equation model
Note. Dotted lines denote non-significant hypotheses, while solid lines show significant relationships.

The mediation analysis results (H8: AA → PU → BI) are summarised in Table 6. The direct effect of AA on BI was .026 (standard error (SE) = .029, 95% CI = [- .028, .081]), which was insignificant as the confidence interval includes zero. In contrast, the indirect effect through PU was .156 (SE = .040, 95% CI = [.082, .240]), indicating a significant mediating role of PU. The total effect of AA on BI was .182 (SE = .046, 95% CI = [.094, .273]), confirming that AA has a positive overall effect on BI. Since the direct effect was not significant, the relationship between AA and BI is primarily explained by the indirect pathway through PU.

Table 6
Mediation analysis results

Effect	Estimate	SE	95% CI	
			Lower 2.5%	Upper 2.5%
Direct effect (AA → BI)	.026	.029	- .028	.081
Indirect effect (AA → PU → BI)	.156***	.040	.082	.240
Total effect	.182***	.046	.094	.273

****p* < .001.

The two open-ended questions collected 285 responses, totalling 17,988 words. After an initial analysis, we generated 47 thematic codes. Following a thorough analysis of these codes and their accompanied quantitative data, 22 codes related to artificial autonomy and risk aversion were selected. These codes were then merged into two main themes: a valuable tool for teaching despite its limited autonomy and a greater risk for learners than for teachers. These themes illuminate the unexpected findings regarding the role of artificial autonomy and risk aversion in teachers' decision to adopt ChatGPT in teaching.

A valuable tool for teaching despite its limited autonomy

Teachers primarily viewed ChatGPT (GPT-3.5 and GPT-4) as semi-autonomous in education, describing it using words such as "auxiliary", "support", "facilitate", "facilitatory", "facilitation", "assist", "assistant", "assistive", "aid", "scaffold", "complement", "complementary", "supplement", "partner", "companion". Sam (a pseudonym) aptly captured this prevalent perception: "AI can only be used to assist and not complete it in its entity". This finding aligns with the quantitative data (see Table 1) that most teachers chose "teacher assistance" and "partial automation" when evaluating the autonomy of ChatGPT in education.

Teachers perceived ChatGPT's semi-autonomous capability as useful in certain teaching scenarios, including crafting materials (e.g., quizzes, syllabi, summaries, rubrics and courseware); streamlining repetitive and mechanical tasks (e.g., grading, marking, editing, administrative duties); and engaging students through simulated debates and addressing queries. However, one participating teacher, Davis (a pseudonym), emphasised that "the decision to adopt ChatGPT should be made on a case-by-case basis", taking into account student needs, disciplinary contexts, task characteristics, intended users (teachers or students) and the timing of use. This situational awareness suggests that adoption decisions were shaped less by artificial autonomy than by contextual and pedagogical considerations, which may help explain the non-significant direct relationship between AA and BI.

A greater risk for learners than for teachers

Teachers' perceptions of ChatGPT-related risks in teaching varied widely. Fifteen teachers expressed no concerns, stressing that education is fundamentally about humans, not tools, and using ChatGPT poses no insurmountable risks. Some acknowledged risks but felt confident managing them due to their tech-savviness and low expectations of ChatGPT's autonomy.

In addition, the risks mentioned by teachers were primarily associated with students' use of ChatGPT. Teachers expressed concerns that ChatGPT may encourage students to use shortcuts, impede their acquisition of foundational knowledge and higher-order thinking skills, expose students to hallucinations, reduce meaningful human interaction in education and introduce complex ethical, legal and equity challenges, including cheating, copyright, data privacy and bias. These findings help explain the insignificant association between RA and PU, where PU was conceptualised and measured as the perceived value of ChatGPT in enhancing teaching quality, productivity, performance and effectiveness. In other words, despite their risk aversion, teachers might still see ChatGPT as valuable for teaching, as their concern primarily lies in students' use of rather than their own.

Conclusion and discussion

To meaningfully navigate this human-AI hybrid landscape, teachers must critically adopt, experiment with and evaluate GenAI in their teaching. However, research indicates varied acceptance of GenAI among educators (Kim et al., 2025; Lee et al., 2024; Miranda & Chamorro-Mera, 2026; Ulla et al., 2023). To understand these variations, this study proposed a conceptual model integrating teachers' perceptions of GenAI's autonomy and their own risk aversion through the lens of human-AI interaction. The results indicate that teachers typically perceive GenAI's autonomy as limited to a semi-autonomous level, preferring to retain full control over the teaching process. Despite automation being a defining feature of AI technology, when teachers have a low expectation of GenAI autonomous capabilities in teaching, their adoption intention is not directly linked to its autonomy. As the appeal of automation waned, concerns about potential harm intensified. The study indicates that risk aversion is a significant determinant of adoption intention. The research findings contribute to the discussion on the human-AI symbiosis and provide valuable guidance for institutions aiming to integrate GenAI or similar AI tools into their educational systems. This section will discuss how the findings address the RQs and their educational implications.

Regarding RQ1, the original model faced low discriminant validity among three constructs: ATT, BI and PU due to high correlations between ATT and the other two constructs. Debates around the role of ATT in TAM have been prevalent in the literature, but no consensus has been reached (López-Bonilla & López-Bonilla, 2011, 2017; Nistor & Heymann, 2010; Teo, 2009; Teo & Noyes, 2011; Ursavaş, 2013). Teo and Noyes (2011) found that removing ATT from TAM significantly improved its model fit. This study further supports the previous finding, as the removal of ATT helps achieve discriminant validity in the measurement model. The refined model explained 79.8% of the variance in BI. In the refined model, five hypotheses were supported (PU → BI, PEU → PU, AA → PU, RA → BI, AA → PU → BI) and the other three were not (PEU → BI, RA → PU, AA → BI).

The associations originally proposed in TAM (PU → BI, PEU → PU) were significant in this study (H1: $\beta = .815$, $p < .001$; H3: $\beta = .501$, $p < .001$), supporting previous empirical findings (An et al., 2023; Choi et al., 2023; Zhang et al., 2023). The modified relationship between PEU and BI was not confirmed in this study (H2: $\beta = .098$, $p > .05$). Xu et al.'s (2018) study on public acceptance of automated vehicles suggested that direct experience with them can strengthen the otherwise weak PEU → BI relationship. Inspired by their study, we conducted a post hoc analysis to retest the refined model by extracting data from 225 participants with experience using AI in teaching (see Appendix B). The analysis revealed a significant association between PEU and BI ($\beta = .138$, $p < .05$). This finding suggests that individuals without direct experience using automated vehicles and GenAI in teaching often assume these to be easy to use, as AI technologies are built to automate tasks. However, with experience interacting with these technologies, they will have a more realistic understanding of the effort required to use them (Ojubanire et al., 2025). In other words, PEU is more critical for users with direct GenAI teaching experience than for those without. Based on this finding, institutions can tailor training programmes accordingly: for those who have not yet used GenAI in their teaching, training should emphasise its pedagogical potentials, while for those with experience, providing teaching examples, scenarios and pedagogical strategies can ease the perceived effort of GenAI adoption (Ojubanire et al., 2025).

For RQ2, the research findings suggest that teachers' perceptions of GenAI's autonomy influenced BI indirectly through PU but showed no direct association with BI. Despite significant advances in AI technologies in recent years, GenAI remains confined to replicating simplified facets of reality, lacking cultural and worldly engagement (Fjelland, 2020). This inherent limitation prevents teachers from perceiving GenAI as a fully autonomous agent, particularly in complex and dynamic settings like education (Zheng et al., 2025). This is evident in participants' responses that they were impressed by GenAI's performance in certain tasks; still, very few endorsed the idea of full autonomy, where GenAI could independently carry out assigned tasks without human intervention. In addition, most AI technologies, including GenAI, are not originally designed for educational purposes (Giannakos et al., 2025; Xu & Ouyang, 2022). Teachers need to "make efforts to make sense of them, work them into the social practices" (Oliver, 2013, p. 41). Integrating GenAI into educational environments requires careful and individualised consideration. The qualitative data further revealed that teachers need to assess various situational factors such as disciplinary differences, student needs, the particularities of teaching and learning tasks, timing and the multiple stakeholders involved in the educational ecosystem. This situational awareness could play a more decisive role influencing teachers' GenAI adoption than their perceptions of GenAI's autonomy in teaching.

In sum, when employed as a teacher assistance to automate specific teaching tasks, GenAI has garnered positive impressions from teachers, who may perceive it as a valuable resource. However, few teachers viewed it as having full autonomy, and humans need to maintain dominance in the human-AI interactions. GenAI adoption involves careful consideration of the unique requirements and circumstances of each educational context (ElSayary, 2023). Thus, it is beneficial to provide examples demonstrating how GenAI can support teaching and learning, tailored to specific contexts, student needs and disciplines.

Regarding RQ3, our findings show that while teachers' risk aversion – the hesitation to engage in risky scenarios – was negatively associated with adoption intention. Qualitative data indicate that although teachers may view GenAI as useful, risk-averse individuals hesitate due to concerns about student misuse. Firat (2023) corroborates this, suggesting reluctance stems from fears that misuse could erode educational standards and compromise academic integrity. We advocate that teachers integrate ChatGPT actively and cautiously into their teaching, as, like other technologies, it brings both educational potential and challenges. For example, Niloy et al. (2024) found that student use of GenAI reduced creativity in content accuracy, originality and similarity, but improved presentability and elaboration. Teachers are encouraged to take a nuanced approach, creatively using GenAI to leverage its strengths.

Research has shown that teachers' risk perceptions can be alleviated by clear support and explicit guidelines (Howard, 2013). Clear policies on safe, effective GenAI use, and risks management strategies, may increase adoption. Institutions can also provide funding and professional development to enhance teachers' AI literacy, introducing AI capabilities, pedagogical strategies and critical evaluation. Integrating AI ethics into curricula and transforming assessment formats are also key to improving educational outcomes while maintaining ethical standards.

Limitations and future study

Researchers should note the following limitations when using these findings. In this study, data were collected through self-reported questionnaires, embedded with open-ended questions to aid in interpreting and extending the quantitative results. Future studies could employ in-depth interviews, focus groups, ethnographic observations or longitudinal design to triangulate these findings, enrich our understanding of how teachers engage with GenAI and track changes over time.

In addition, respondents completed the survey online, perhaps showing higher digital literacy and more favourable perceptions of GenAI than other teacher groups. Future research is advised to test the validity of the proposed model across diverse teacher populations to ensure broader applicability and relevance in evolving institutional environments.

Future research could also explore how factors such as gender, technological confidence, teaching experience and disciplinary background moderate the link between teachers' perceptions and their intention to integrate AI into teaching, offering nuanced insights into the underlying psychological processes leading to AI adoption. Additionally, comparative studies across cultures could reveal cultural-specific and universal factors influencing teachers' acceptance of AI tools like GenAI.

Author contributions

Hai Min Dai: Conceptualisation, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Validation, Visualisation, Writing – original draft, Writing – review and editing; **Kaige Ni:** Data curation, Formal analysis, Investigation, Software, Validation, Visualisation, Writing – original draft, Writing – review and editing; **Han Meng:** Data curation, Formal analysis, Investigation, Software, Validation, Visualisation, Writing – original draft, Writing – review and editing; **Bei Ju:** Writing – review and editing; **Joseph Crawford:** Writing – review and editing; **Timothy Teo:** Writing – review and editing.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Young Scientists Fund) (Grant No. 72504179) and the 2023 Humanities and Social Science Research Grant (Young Researcher Fund) by the Ministry of Education of the People's Republic of China (Grant No. 23YJC880015).

References

Adeshola, I., & Adepoju, A. P. (2023). The opportunities and challenges of ChatGPT in education. *Interactive Learning Environments, 32*(10), 6159–6172. https://doi.org/10.1080/10494820.2023.2253858

Al Darayseh, A. (2023). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Computers and Education: Artificial Intelligence, 4,* Article 100132. https://doi.org/10.1016/j.caeai.2023.100132

An, X., Chai, C. S., Li, Y., Zhou, Y., Shen, X., Zheng, C., & Chen, M. (2023). Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. *Education and Information Technologies, 28*, 5187–5208. https://doi.org/10.1007/s10639-022-11286-z

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*(1), Article 10. https://doi.org/10.1186/s41239-025-00507-3

Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Beer, J. M., Fisk, A. D., & Rogers, W. A. (2014). Toward a framework for levels of robot autonomy in human-robot interaction. *Journal of Human-Robot Interaction, 3*(2), 74–99. https://doi.org/10.5898/JHRI.3.2.Beer

Bøe, T., Gulbrandsen, B., & Sørebø, Ø. (2015). How to stimulate the continued use of ICT in higher education: Integrating information systems continuance theory and agency theory. *Computers in Human Behavior, 50,* 375–384. https://doi.org/10.1016/j.chb.2015.03.084

Boulus-Rødje, N., Cranefield, J., Doyle, C., & Fleron, B. (2024). GenAI and me: The hidden work of building and maintaining an augmentative partnership. *Personal and Ubiquitous Computing, 28*(6), 861–874. https://doi.org/10.1007/s00779-024-01810-y

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies, 25,* 3443–3463. https://doi.org/10.1007/s10639-020-10159-7

Choi, S., Jang, Y., & Kim, H. (2023). Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools. *International Journal of Human-Computer Interaction, 39*(4), 910–922. https://doi.org/10.1080/10447318.2022.2049145

Cotton, D. R., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International, 61*(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Cukurova, M., Kent, C., & Luckin, R. (2019). Artificial intelligence and multimodal data in the service of human decision-making: A case study in debate tutoring. *British Journal of Educational Technology, 50*(6), 3032–3046. https://doi.org/10.1111/bjet.12829

Darvishi, A., Khosravi, H., Sadiq, S., Gašević, D., & Siemens, G. (2024). Impact of AI assistance on student agency. *Computers & Education, 210*, Article 104967. https://doi.org/10.1016/j.compedu.2023.104967

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Eager, B., & Brunton, R. (2023). Prompting higher education towards AI-augmented teaching and learning practice. *Journal of University Teaching & Learning Practice, 20*(5), 1–19. https://doi.org/10.53761/1.20.5.02

ElSayary, A. (2023). An investigation of teachers' perceptions of using ChatGPT as a supporting tool for teaching and learning in the digital era. *Journal of Computer Assisted Learning, 40*(3), 931–945. https://doi.org/10.1111/jcal.12926

Endsley, M. R., & Kaber, D. B. (1999). Level of automation effects on performance, situation awareness and workload in a dynamic control task. *Ergonomics, 42*(3), 462–492. https://doi.org/10.1080/001401399185595

Firat, M. (2023). What ChatGPT means for universities: Perceptions of scholars and students. *Journal of Applied Learning and Teaching, 6*(1), 57–63. https://doi.org/10.37074/jalt.2023.6.1.22

Fjelland, R. (2020). Why general artificial intelligence will not be realized. *Humanities and Social Sciences Communications, 7*, Article 10. https://doi.org/10.1057/s41599-020-0494-4

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.2307/3151312

Fox, C. R., Erner, C., & Walters, D. J. (2015). D*ecision under risk: From the field to the laboratory and back*. In G. Keren & G. Wu (Eds.), *The Wiley Blackwell handbook of judgment and decision making* (pp. 41–88). John Wiley & Sons. https://doi.org/10.1002/9781118468333.ch2

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Giannakos, M., Azevedo, R., Brusilovsky, P., Cukurova, M., Dimitriadis, Y., Hernandez-Leo, D., Järvelä, S., Mavrikis, M., & Rienties, B. (2025). The promise and challenges of generative AI in education. *Behaviour & Information Technology*, *44*(11), 2518–2544. https://doi.org/10.1080/0144929X.2024.2394886

Granić, A. (2022). Technology acceptance and adoption in education. In O. Zawacki-Richter & I. Jung (Eds.), *Handbook of open, distance and digital education* (pp. 1–15). Springer. https://doi.org/10.1007/978-981-19-0351-9_89-1

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall.

Henderson, J., & Corry, M. (2021). Teacher anxiety and technology change: A review of the literature. *Technology, Pedagogy and Education, 30*(4), 573–587. https://doi.org/10.1080/1475939X.2021.1931426

Holstein, K., & Aleven, V. (2022). Designing for human-AI complementarity in K-12 education. *AI Magazine, 43*(2), 239–248. https://doi.org/10.1002/aaai.12058

Howard, S. K. (2011). Affect and acceptability: Exploring teachers' technology-related risk perceptions. *Educational Media International, 48*(4), 261–272. https://doi.org/10.1080/09523987.2011.632275

Howard, S. K. (2013). Risk-aversion: Understanding teachers' resistance to technology integration. *Technology, Pedagogy and Education, 22*(3), 357–372. https://doi.org/10.1080/1475939X.2013.802995

Howard, S. K., & Mozejko, A. (2015). Teachers: technology, change and resistance. *Teaching and Digital Technologies: Big Issues and Critical Questions, 2*(1), 307–317. https://doi.org/10.1017/CBO9781316091968.030
Hu, Q., Lu, Y., Pan, Z., Gong, Y., & Yang, Z. (2021). Can AI artifacts influence human cognition? The effects of artificial autonomy in intelligent personal assistants. *International Journal of Information Management, 56,* Article 102250. https://doi.org/10.1016/j.ijinfomgt.2020.102250
Jiang, T., Sun, Z., Fu, S., & Lv, Y. (2024). Human-AI interaction research agenda: A user-centered perspective. *Data and Information Management, 8*(4), Article 100078. https://doi.org/10.1016/j.dim.2024.100078
Jiang, Y., Hao, J., Fauss, M., & Li, C. (2024). Detecting ChatGPT-generated essays in a large-scale writing assessment: Is there a bias against non-native English speakers? *Computers & Education, 217,* Article 105070. https://doi.org/10.1016/j.compedu.2024.105070
Jose, B., Cherian, J., Verghis, A. M., Varghise, S. M., S, M., & Joseph, S. (2025). The cognitive paradox of AI in education: Between enhancement and erosion. *Frontiers in Psychology, 16*, Article 1550621. https://doi.org/10.3389/fpsyg.2025.1550621
Kelly, S., Kaye, S. A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics, 77,* Article 101925. https://doi.org/10.1016/j.tele.2022.101925
Kim, J., Klopfer, M., Grohs, J. R., Eldardiry, H., Weichert, J., Cox, L. A., II, & Pike, D. (2025). Examining faculty and student perceptions of generative AI in university courses. *Innovative Higher Education*, *50*(4), 1281–1313. https://doi.org/10.1007/s10755-024-09774-w
King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003
Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). Guilford Press.
Kostopoulos, G., Gkamas, V., Rigou, M., & Kotsiantis, S. (2025). Agentic AI in education: State of the art and future directions. *IEEE Access, 13,* 177467–177491. https://doi.org/10.1109/ACCESS.2025.3620473
Lee, D., Arnold, M., Srivastava, A., Plastow, K., Strelan, P., Ploeckl, F., ... & Palmer, E. (2024). The impact of generative AI on higher education learning and teaching: A study of educators' perspectives. *Computers and Education: Artificial Intelligence, 6*, Article 100221. https://doi.org/10.1016/j.caeai.2024.100221
Lilleholt, L. (2019). Cognitive ability and risk aversion: A systematic review and meta analysis. *Judgment and Decision Making, 14*(3), 234–279. https://doi.org/10.1017/S1930297500004307
López-Bonilla, L. M., & López-Bonilla, J. M. (2011). The role of attitudes in the TAM: A theoretically unnecessary construct? *British Journal of Educational Technology, 42*(6), E160–E162. https://doi.org/10.1111/j.1467-8535.2011.01232.x
López-Bonilla, L. M., & López-Bonilla, J. M. (2017). Explaining the discrepancy in the mediating role of attitude in the TAM. *British Journal of Educational Technology, 48*(4), 940–949. https://doi.org/10.1111/bjet.12465
Lyu, W., Zhang, S., Chung, T., Sun, Y., & Zhang, Y. (2025). Understanding the practices, perceptions, and (dis)trust of generative AI among instructors: A mixed-methods study in U.S. higher education. *Computers and Education: Artificial Intelligence, 8*, Article 100383. https://doi.org/10.1016/j.caeai.2025.100383
Mandrik, C. A., & Bao, Y. (2005). Exploring the concept and measurement of general risk aversion. In G. Menon & A. R. Rao (Eds.), *Advances in consumer research* (Vol. 32, pp. 531–539). Association for Consumer Research.
Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society, 14*, 81–95. https://doi.org/10.1007/s10209-014-0348-1
Molenaar, I. (2022). Towards hybrid human-AI learning technologies. *European Journal of Education, 57*(4), 632–645. https://doi.org/10.1111/ejed.12527
Miranda, F. J., & Chamorro-Mera, A. (2026). Exploring the adoption of generative artificial intelligence tools among university teachers. *Higher Education Research & Development*, *45*(3), 680–696. https://doi.org/10.1080/07294360.2025.2559648

Niloy, A. C., Akter, S., Sultana, N., Sultana, J., & Rahman, S. I. U. (2024). Is Chatgpt a menace for creative writing ability? An experiment. *Journal of Computer Assisted Learning, 40*(2), 919–930. https://doi.org/10.1111/jcal.12929

Nistor, N., & Heymann, J. O. (2010). Reconsidering the role of attitude in the TAM: An answer to Teo (2009a). *British Journal of Educational Technology, 41*(6), E142–E146. https://doi.org/10.1111/j.1467-8535.2010.01109.x

OECD. (2026). *OECD digital education outlook 2026: Exploring effective uses of generative AI in education.* https://doi.org/10.1787/062a7394-en

Oliver, M. (2013). Learning technology: Theorising the tools we study. *British Journal of Educational Technology*, *44*(1), 31–43. https://doi.org/10.1111/j.1467-8535.2011.01283.x

Ojubanire, O. A., Olaleye, A. S., Marhraoui, M. A., Kamihanda, M. W., Oke, O. I., & Ojubanire, O. A. (2025). Awareness, perception, and adoption of ChatGPT in African HEIs: A multi-dimensional analysis. *The Internet and Higher Education, 65,* Article 100999. https://doi.org/10.1016/j.iheduc.2025.100999

Palan, S., & Schitter, C. (2018). Prolific.ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance, 17,* 22–27. https://doi.org/10.1016/j.jbef.2017.12.004

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems Man and Cybernetics Part A: Systems and Humans, 30*(3), 286–297. https://doi.org/10.1109/3468.844354

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://psycnet.apa.org/doi/10.1037/0021-9010.88.5.879

Pratt, J. W. (1978). Risk aversion in the small and in the large. In P. Diamond & M. Rothschild (Eds.), *Uncertainty in economics* (pp. 59–79). *Academic Press*. https://doi.org/10.1016/B978-0-12-214850-7.50010-3

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic methods for the direct and indirect effects: Introduction to the special issue on mediation analysis. *Multivariate Behavioral Research, 43*(3), 211–222. https://doi.org/10.3758/BRM.40.3.879

Raykov, T., & Marcoulides, G. A. (2008). *An introduction to applied multivariate analysis.* Routledge. https://doi.org/10.4324/9780203809532

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education, 128,* 13–35. https://doi.org/10.1016/j.compedu.2018.09.009

Scherer, R., & Teo, T. (2019). Unpacking teachers' intentions to integrate technology: A meta-analysis. *Educational Research Review*, *27*, 90–109. https://doi.org/10.1016/j.edurev.2019.03.001

Šedlbauer, J., Činčera, J., Slavík, M., & Hartlová, A. (2024). Students' reflections on their experience with ChatGPT. *Journal of Computer Assisted Learning, 40*(4), 1526–1534. https://doi.org/10.1111/jcal.12967

Sheridan, T. B., & Verplank, W. L. (1978). Human/computer control of undersea teleoperators. In *Proceedings of the 14th Annual Conference on Manual Control* (pp. 343–357). NASA Ames Research Center. https://ntrs.nasa.gov/citations/19790007441

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(2), 144–176. https://doi.org/10.1287/isre.6.2.144

Teo, T. (2009). Is there an attitude problem? Reconsidering the role of attitude in the TAM. *British Journal of Educational Technology, 40*(6), 1139–1141. https://doi.org/10.1111/j.1467-8535.2008.00913.x

Teo, T., & Noyes, J. (2011). An assessment of the influence of perceived enjoyment and attitude on the intention to use technology among pre-service teachers: A structural equation modelling approach. *Computers & Education, 57*(2), 1645–1653. https://doi.org/10.1016/j.compedu.2011.03.002

Tran, T. M., Bakajic, M., & Pullman, M. (2025). Teacher’s pet or rebel? Practitioners’ perspectives on the impacts of ChatGPT on course design. *Higher Education*, *90*, 777–800. https://doi.org/10.1007/s10734-024-01350-7

Ulla, M. B., Perales, W. F., & Busbus, S. O. (2023). ‘To generate or stop generating response’: Exploring EFL teachers’ perspectives on ChatGPT in English language teaching in Thailand. *Learning: Research and Practice, 9*(2), 168–182. https://doi.org/10.1080/23735082.2023.2257252

UNESCO Institute for Statistics. (2014). *ISCED fields of education and training 2013 (ISCED–F 2013): Manual to accompany the International Standard Classification of Education 2011.* https://unesdoc.unesco.org/ark:/48223/pf0000228085_eng

Ursavaş, Ö. F. (2013). Reconsidering the role of attitude in the TAM: An answer to Teo (2009) and Nistor and Heymann (2010), and Lopez-Bonilla and Lopez-Bonilla (2011). *British Journal of Educational Technology, 44*(1), E22–E25. https://doi.org/10.1111/j.1467-8535.2012.01327.x

Uysal, E., Alavi, S., & Bezençon, V. (2023). Anthropomorphism in artificial intelligence: A review of empirical work across domains and insights for future research. In K. Sudhir & O. Toubia (Eds.), *Review of Marketing Research: Vol. 20. Artificial intelligence in marketing* (pp. 273–308). Emerald Publishing Limited. https://doi.org/10.1108/s1548-643520230000020015

Wang, J., & Wang, X. (2019). S*tructural equation modeling: Applications using Mplus*. John Wiley & Sons. https://doi.org/10.1002/9781119422730

Webb, M., & Galamba, A. (2026). Transforming pedagogy with GenAI-supported formative assessment: Challenges for teacher education. *British Journal of Educational Technology, 57*(3), 690–706. https://doi.org/10.1111/bjet.70051

Wong, L. H., Park, H., & Looi, C. K. (2024). From hype to insight: Exploring ChatGPT's early footprint in education via altmetrics and bibliometrics. *Journal of Computer Assisted Learning, 40*(4), 1428–1446. https://doi.org/10.1111/jcal.12962

Xu, W., & Ouyang, F. (2022). A systematic review of AI role in the educational system based on a proposed conceptual framework. *Education and Information Technologies, 27*(3), 4195–4223. https://doi.org/10.1007/s10639-021-10774-y

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., & Liu, P. (2018). What drives people to accept automated vehicles? Findings from a field experiment. *Transportation Research Part C: Emerging Technologies, 95,* 320–334. https://doi.org/10.1016/j.trc.2018.07.024

Xue, L., Mahat, J., & Ghazali, N. (2026). Technology acceptance model in artificial intelligence in education: A meta–analysis. *Sage Open*, *16*(1), Article 21582440251409441. https://doi.org/10.1177/21582440251409441

Yang, H. (2023, April 12). How I use ChatGPT responsibly in my teaching. *Nature.* https://doi.org/10.1038/d41586-023-01026-9

Zawacki-Richter, O., & Jung, I. (2023). Shaping the field of open, distance, and digital education: An introduction. In O. Zawacki-Richter & I. Jung (Eds.). *Handbook of open, distance and digital education* (pp. 3–12). Springer. https://doi.org/10.1007/978-981-19-2080-6_94

Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: A multigroup analysis. *International Journal of Educational Technology in Higher Education, 20*, Article 49. https://doi.org/10.1186/s41239-023-00420-7

Zhang, L., & Xu, J. (2025). The paradox of self-efficacy and technological dependence: Unraveling generative AI’s impact on university students’ task completion. *The Internet and Higher Education, 65,* Article 100978. https://doi.org/10.1016/j.iheduc.2024.100978

Zheng, L., Jiang, F., Gu, X., Li, Y., Wang, G., & Zhang, H. (2025). Teaching via LLM-enhanced simulations: Authenticity and barriers to suspension of disbelief. *The Internet and Higher Education, 65*, Article 100990. https://doi.org/10.1016/j.iheduc.2024.100990

Zhou, X., Zhang, J., & Chan, C. (2024). Unveiling students’ experiences and perceptions of artificial intelligence usage in higher education. *Journal of University Teaching and Learning Practice, 21*(6), 126–145. https://doi.org/10.53761/xzjprb2

Corresponding author: Han Meng, maxmeng07@sjtu.edu.cn

Please cite as: Dai, H. M., Ni, K., Meng, H., Ju, B., Crawford, J., & Teo, T. (2026). GenAI as a frenemy in teaching: Perceived autonomy and risks. *Australasian Journal of Educational Technology*, *42*(3), 157–179. https://doi.org/10.14742/ajet.11301

Appendix A: Questionnaire items

Behavioural intention (Chatterjee & Bhattacharjee, 2020; Choi et al., 2023)

BI1. Given that I had access to ChatGPT, I predict that I would use it for teaching.
BI2. I plan to use ChatGPT for teaching in the future.
BI3. I will use ChatGPT for teaching on a regular basis in the future.
BI4. I will use ChatGPT for teaching frequently in the future.

Perceived ease of use (An et al., 2023; Chatterjee & Bhattacharjee, 2020)

PEU1. ChatGPT is easy to operate for me.
PEU2. I can easily master the skills of using ChatGPT for teaching.
PEU3. My interaction with ChatGPT is clear and understandable.
PEU4. I find it easy to get ChatGPT to do what I want it to do.

Perceived usefulness (An et al., 2023; Chatterjee & Bhattacharjee, 2020)

PU1. ChatGPT can help me improve the quality of teaching.
PU2. Using ChatGPT would increase my productivity in teaching.
PU3. Using ChatGPT would improve my performance in teaching.
PU4. Using ChatGPT would enhance my effectiveness in teaching.

Risk aversion (Mandrik & Bao, 2005)

RA1. I prefer situations that have foreseeable outcomes.
RA2. Before I make a decision, I like to be absolutely sure how things will turn out.
RA3. I avoid situations that have uncertain outcomes.

Attitude (Taylor & Todd, 1995)

ATT1. ChatGPT makes teaching more interesting.
ATT2. Teaching with ChatGPT is fun.
ATT3. Using ChatGPT for teaching is a good idea.
ATT4. I dislike the idea of using ChatGPT for teaching.

Artificial autonomy (Molenaar, 2022)

The illustration provided below depicts the allocation of responsibilities among teachers, students and AI across six distinct levels. As we move from left to right, there is a progressive reduction in the extent of teacher involvement, accompanied by a corresponding increase in the prominence of AI involvement.

Kindly CHOOSE the level that best represents your perception regarding the role of ChatGPT in education.

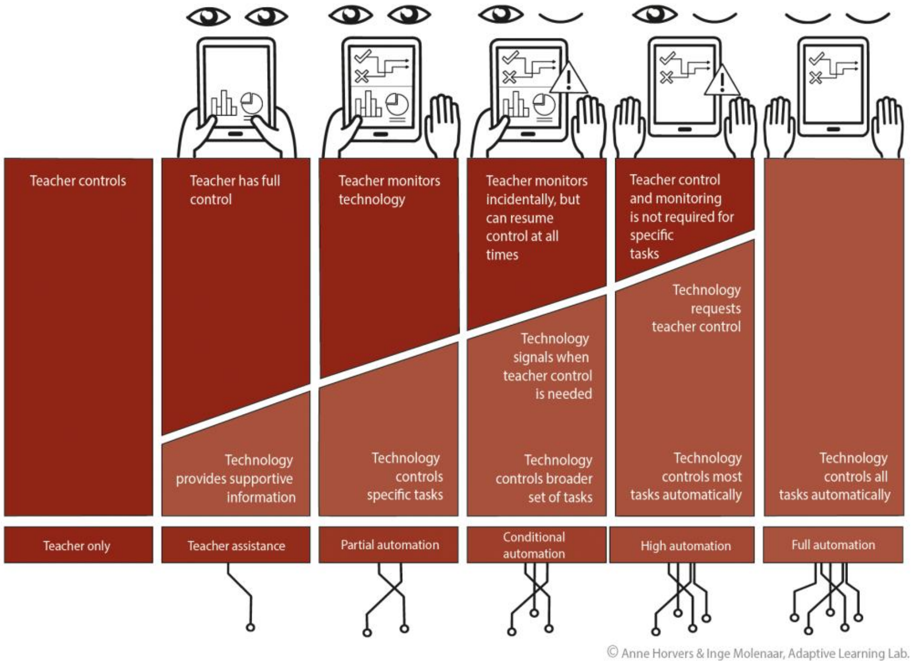

Figure A1. The six-level model of automation
Note. The chart illustrates that higher artificial autonomy correlates with more data sources (dots at the bottom). The eyes at the top symbolise teacher supervision and the hands represent teacher control over teaching arrangements (Horvers & Molenaar, 2022, as cited in Molenaar, 2022).

Appendix B: Post hoc analysis

The univariate normality of all observed variables was assessed by examining skewness and kurtosis values. In this data set, which includes 225 participants who had experience integrating AI into teaching, the skewness values varied between -1.295 and -.250, while kurtosis values were observed between -0.759 and 2.100. Since the absolute values of skewness and kurtosis were below the recommended thresholds of 3.0 and 8.0, respectively, univariate normality was confirmed (Kline, 2011). However, multivariate normality was not supported, as indicated by Mardia's coefficient of 347.805, which exceeded the threshold of 272 calculated from the formula $p(p + 2)$, where p represents the number of observed variables (Raykov & Marcoulides, 2008). Consequently, the maximum likelihood robust estimator in Mplus 7 was selected as the estimation method, providing robustness in non-normal data sets (Wang & Wang, 2019).

Convergent validity was confirmed through the values of composite reliability (CR) greater than .60 (Hair et al., 2010), Cronbach's alpha exceeding .70, and average variance extracted (AVE) above .50 (Fornell & Larcker, 1981) (see Table B1). In addition, all constructs' square root of AVE exceeded their correlations with other constructs, hence discriminant validity was supported (Fornell & Larcker, 1981) (see Table B2).

Table B1
Convergent validity (n = 225)

Constructs	Item	*M*	*SD*	Standardised loading	CR	AVE	Cronbach's alpha
Behavioural intention	BI1	5.76	1.277	.938	.948	.819	.945
	BI2	5.68	1.281	.942			
	BI3	5.37	1.341	.872			
	BI4	5.12	1.460	.866			
Perceived usefulness	PU1	5.13	1.352	.875	.937	.788	.936
	PU2	5.28	1.377	.860			
	PU3	4.92	1.378	.898			
	PU4	5.20	1.390	.916			
Perceived ease of use	PEU1	5.71	1.150	.695	.852	.591	.851
	PEU2	5.34	1.196	.813			
	PEU3	5.48	1.126	.830			
	PEU4	5.06	1.158	.729			
Risk aversion	RA1	4.79	1.295	.761	.802	.577	.797
	RA2	4.91	1.345	.672			
	RA3	4.35	1.540	.836			

Table B2
Discriminant validity

	BI	PU	PEU	RA
BI	**.905**			
PU	.867***	**.888**		
PEU	.536***	.517***	**.769**	
RA	-.175*	-.024	.078	**.760**

Note. BI = behavioural intention; PU = perceived usefulness; PEU = perceived ease of use; RA = risk aversion. The diagonal elements are the square roots of AVE, and the off-diagonal elements are inter-construct correlations. The correlations between RA and PU, and between RA and PEU, were not statistically significant.
*p < .05, **p < .01, ***p < .001.

A common latent factor (CLF) was used to capture the common variance among the observed variables before assessing the overall fitness of the measurement model. A comparison between the standardised regression weights from the model with CLF and those from the model without CLF suggested no issue of common method bias (Podsakoff et al., 2003). The measurement model achieved an acceptable model fit [χ^2 (84) = 168.547 (p < .001), χ^2/df = 2.007, CFI = .961, TLI = .951, RMSEA = .067 and SRMR = .038], as all indices met the guidelines suggested by Hair et al. (2010), that is, χ^2/df < 5, CFI > .90; TLI > .90; RMSEA < .08; SRMR < .08. The structural model also achieved an acceptable model fit [χ^2 (97) = 185.129 (p < .001), χ^2/df = 1.909, CFI = .961, TLI = .952, RMSEA = .064 and SRMR = .047]. All structural path estimates were significant except for the relationship between RA and PU. The structural model explained 78.7% of the variance in BI. The hypothesis testing results are presented in Table B3 and Figure B1.

Table B3
Test results

No.	Hypothesised relation	Standardised estimates	Test results
H1	PU → BI	.787***	Supported
H2	PEU → BI	.138*	Supported
H3	PEU → PU	.504***	Supported
H4	AA → PU	.141**	Supported
H5	AA → BI	.045	**Unsupported**
H6	RA → PU	-.054	**Unsupported**
H7	RA → BI	-.167**	Supported

Note. PU = perceived usefulness; BI = behavioural intention; PEU = perceived ease of use; AA = artificial autonomy; RA = risk aversion.
*p < .05, **p < .01, ***p < .001.

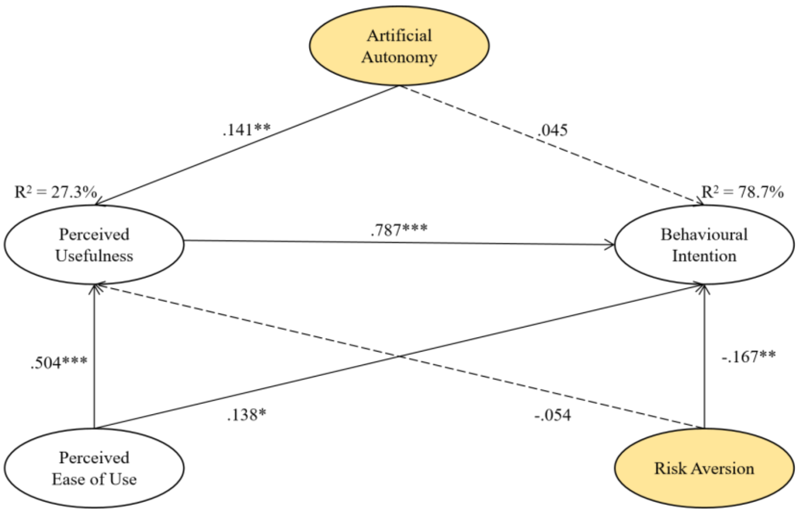

Figure B1. Test results