

PRIVACY CONCERNS AND AI HALLUCINATION RISKS IN GENERATIVE AI CONTINUANCE FOR SELF-DIRECTED LEARNING

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Abstract

The determinants for continuance intention to use generative artificial intelligence (GenAI) for self-directed learning activities are explored. The research incorporates the Technology Acceptance Model (TAM), adding privacy concern and perceived risk of AI hallucination as factors that hinder adoption, and attitude toward using GenAI as a mediator. The study employed a quantitative method by using an online survey that was sent to respondents who were postgraduate students and employees of government institutions involved in using GenAI for self-directed learning. The 100 valid responses were analyzed with the Partial Least Squares Structural Equation Modeling (PLS-SEM) method by using the software SmartPLS 4. The results show that attitude towards the GenAI use has a significant positive impact on continuance intention, and Privacy concern has a significant negative impact on continuance intention. The perceived risk of AI hallucination, however, has no significant impact on attitude and continuance intention. Furthermore, the results suggest that the relationship between privacy concern and continuance intention is not mediated by attitude, and the same applies for the relationship between AI hallucination risk and continuance intention. These findings indicate that the issue of data privacy outweighs technical errors or inaccuracies in the GenAI system in determining continued use for self-directed learning. The study highlights the importance of strengthening privacy protection policies and improving AI literacy to support sustainable GenAI usage in educational contexts.

1. INTRODUCTION

Large Language Models (LLMs) like ChatGPT and Gemini, Claude and Copilot are used to support data analysis and problem solving and are examples of Generative Artificial Intelligence (GenAI). GenAI's characteristics of being able to quickly provide knowledge and package it into various formats are suitable for helping individual in self-directed learning. Self-directed learning is the learning process in which the learner diagnoses learning needs, formulates learning objectives, seeks learning materials, selects learning strategies and assesses the results of learning based on the theory developed by Knowles (1975). In this case, GenAI can act as a virtual assistant that offers a personalized and adaptive learning experience that can be tailored to each individual's needs and preferences (Bozkurt & Sharma, 2023).

In terms of GenAI, adoption and continuance intention (CI) is greatly influenced by mitigating privacy concerns (PRIV) and technological risks (Jo, 2024). Users might be concerned about how their data is stored, processed and used by platform developers, as they require inputting prompts to use GenAI (Dwivedi et al., 2023).

At the same time, in the field of information systems, it is known that when users perceive high risk of data loss, it can lead them to have less trust in the technology (Belanger & Crossler, 2011).

Another revealed risk factor is AI hallucination risk (HAL). HAL is the likelihood that the system makes error, misleading or outright false claims in the form of citations, facts, or references in the answers it provides (Lim et al., 2025). With people involved in self-directed learning, who will not have a teacher to validate information, HAL is a major barrier in the learning process.

The concept of technology acceptance in this study is an adapted version of the Technology Acceptance Model (TAM). TAM emphasizes the psychological aspects that influence a person's attitude toward using (ATT) and behavioral intention to accept a technology (Davis, 1989). Although TAM has shown consistent explanatory power in predicting technology adoption, the model overlooking various potential risks that could affect users' behavior and decision-making processes (Lim et al., 2025). The role of human agencies like motivational factors in the framework is missing (Bagozzi, 2007). Furthermore, previous research on SDL using GenAI has mostly adopted qualitative methods (Isaeva et al., 2026; Kukreja et al., 2025; Yogi et al., 2024) and original TAM quantitative methods (Asag & Al Mamun, 2026; Şimşek et al., 2025; Xia, 2025), without considering the role of perceived risk.

For the sake of this study, the gap was filled by the modification of TAM, which added perceived risk into the model, with the addition of PRIV and HAL. This study will test the proposed acceptance model for GenAI with the addition of risk assessment, which will examine risk assessment's influence on CI of GenAI for self-directed learning through ATT.

2. LITERATURE REVIEW

2.1 Theoretical and Conceptual Background

2.1.1 Privacy concern (PRIV)

One of the biggest challenges to general adoption of AI technologies is the worry about how data may be used. In the academic sectors of developing countries, privacy issues have a significant negative correlation that can deter individuals' intentions to adopt AI tools (Rana et al., 2024). In the same way, in legal services, PRIV directly impacts on user satisfaction when engaging with AI-powered legal contract generation technologies (Q. Wang et al., 2025). The younger generation is especially concerned with personal information that is out of their control, potential for massive data breaches, and potential misuse of their profiles by AI (Shrestha et al., 2024).

The imbalance in perceived privacy risks and benefits of GenAI can contribute to a psychological state of CI, including reactance and information avoidance (Y. Wang et al., 2025). Some studies note that users are paradoxically not confident in privacy policies with GenAI but still interact with chatbots and virtual assistants (Olatunde & Shalan, 2025). This paradox is characterized as the phenomenon of people's actions with their personal information on the Internet, even though they claim to be concerned about privacy (Memarian et al., 2025). In the case of Artificial Intelligence of Things (AIoT) smart home devices, users often prioritize convenience and the functionality of the services over privacy considerations (Liang & Shi, 2025). The paradox further comes into play when considering the balance between the free social media platforms and the risks of privacy that come with AI-powered targeted ads (Uwayezu et al., 2026).

2.1.2 AI hallucination risk (HAL)

AI hallucination refers to the generation of outputs that are either factually incorrect, misleading, or nonsensical in the form of fluent text by GenAI (Ariso & Bannister, 2025). In the field of education, HAL is called structurally well-formed linguistic outputs which include inaccurate facts (Virvou et al., 2025). In general terms, misleading or even outright inaccurate findings generated by GenAI models are known as HAL (Leventi-Peetz & Zacharis, 2025).

The meaning and implications of HAL are varied for different fields of application. In the learning journey, HAL poses an epistemic risk in the sense that learners may uncritically take AI-generated information as true and assimilate it (Virvou et al., 2025). The legal field is one of the areas where GenAI language models often produce inaccurate information, known as hallucination, because they lack specialized training data for direct impact on legal applications (Wan et al., 2024). AI hallucinations can appear, for instance, as pathogenicity predictions for variants, or as a wrong summary of the genetic variant, which can only be counterbalanced by including validated genetic variant data, as demonstrated by Du et al. (2026).

However, it should be noted that the nature of AI hallucination is not always negative; in de novo protein design, algorithmic hallucinations are considered as blueprints for the future: they can open the door to the discovery of novel organisms or proteins (Leventi-Peetz & Zacharis, 2025).

2.1.3 Attitude towards using (ATT) and continuance intention (CI) of GenAI

ATT is always one of the major factors and predictors of CI. Researchers have investigated the impact of experienced users with GenAI and found that a positive ATT for the technology greatly affects and enhances CI (Moon, 2024). In higher education settings, the positive ATT evaluations by students directly affect their CI to use GenAI (Singh & Paiva, 2025). A robust CI, in turn, results in a positive effect on the actual use of GenAI technologies in the teaching and learning processes (Singh & Paiva, 2025).

The design profession has seen a clear impact of designers' ATT and subjective norms on their intention to integrate GenAI into their design processes (Kim & Kim, 2025). In Chinese painters, ATT is closely related to the CI, as are emotional experience and satisfaction levels, and it has a strong influence on CI regarding AI-based painting tools (Xu et al., 2024).

GenAI ATT is extremely vulnerable to the perception of technical and psychological risks, although it is a key factor in predicting CI. If users think that GenAI can produce fake news, it is badly affecting the users' ATT (Moon, 2024). It has also been demonstrated that awareness of possible bias of GenAI systems negatively impacts overall ATT (Moon, 2024). Although privacy concern (PRIV) is not directly related to CI, these concerns can negatively influence users' perspectives and ATT toward AI (Moon, 2024). These technical constraints and academic ethical issues have been considered as important moderator variables that can affect the relationship between ATT and the resulting CI (Verma et al., 2025). Emotional attitude and reaction, especially AI anxiety become the basic factors to determine acceptance and CI rates for creative industry actors (Yin et al., 2023).

2.2 Hypothesis

Overall, there are four latent variables depicted in Figure 1. There are two exogenous variables: privacy concern (PRIV) and perceived risk of AI hallucination (HAL). The other two are endogenous variables, with attitude towards using GenAI (ATT) as the mediating variable and continuance intention (CI) as the main dependent variable.

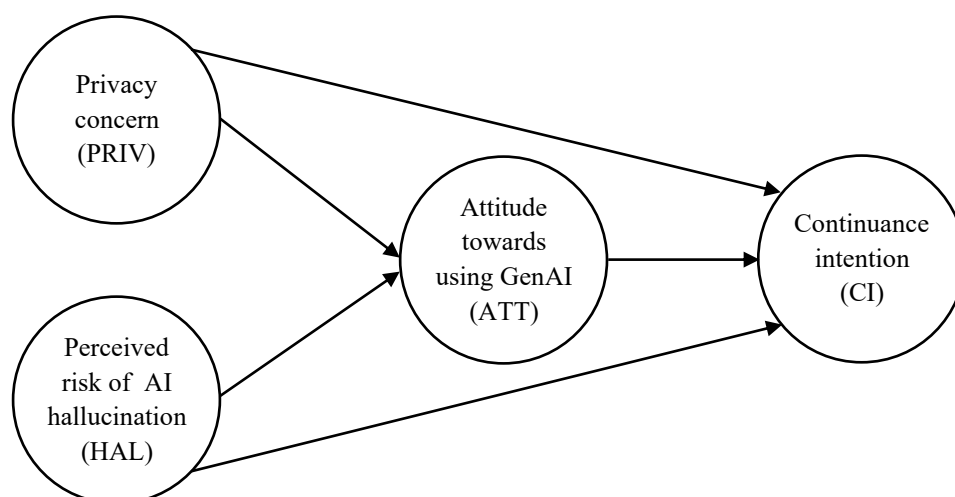


Figure 1. Research Model

Source : Authors (2026)

Each latent variable is measured through a series of observable indicators. Specifically, PRIV is measured by four indicators (PRIV1, PRIV2, PRIV3, PRIV4), and HAL is measured by three indicators (HAL1, HAL2, HAL3). Meanwhile, ATT is measured by three indicators (ATT1, ATT2, ATT3), and CI is measured by three indicators (CI1, CI2, CI3).

Higher privacy risk reduces user trust, which directly lowers ATT (Lim et al., 2025; Santoso & Pangestu, 2026; Song & Tan, 2025). At the same time, PRIV significantly reduces CI (Huynh, 2025; Lee et al., 2025; Lim et al., 2025). Meanwhile, HAL increases cognitive load and negative emotions, which reduces ATT (Liu et al., 2026; Song & Tan, 2025). HAL also reduces the intention to keep using the system (Rejón-Guardia et al., 2026; Shen et al., 2025; Zhang et al., 2026). Thus, the following hypotheses are proposed:

H1: PRIV negatively affects ATT.

H2: PRIV negatively affects CI.

H3: HAL negatively affects ATT.

H4: HAL negatively affects CI.

ATT acts as a main predictor and a mediator for CI. A positive ATT is a strong predictor of higher CI (Arpaci et al., 2026; Lim et al., 2025; Shi et al., 2026). As a mediator, ATT explains the negative impact of risk on CI. The negative effect of PRIV on CI is significantly mediated by a lower ATT (Lee et al., 2025; Lim et al., 2025). Similarly, ATT mediates the negative effect of HAL on CI (Lim et al., 2025; Liu et al., 2026). Thus, the following hypotheses are proposed:

H5: ATT positively affects CI.

H6: ATT mediates the negative effect of PRIV on CI.

H7: ATT mediates the negative effect of HAL on CI.

3. RESEARCH METHODOLOGY

The approach of this study is quantitative approach and a survey method. This study's population consists of all the users of GenAI for self-directed learning. The respondents were selected by purposive sampling, which is a sample selection technique based on predetermined criteria in order to be representative of the research target (Sugiyono, 2018), namely students who are studying at the Financial Education and Training Agency (BPPK) and students who are studying at Jakarta State University (UNJ). The selection of these two target groups is because of the fact that postgraduate academics and professionals in the government institutions are relevant target groups that are active in the use of digital technology, particularly GenAI to facilitate daily tasks (Arowosegbe et al., 2024; Bright et al., 2025; Maphosa et al., 2026; Simaremare et al., 2024; Tangi et al., 2026). This corroborates the validity of continuance intention research which is based on post-adoption experience (Bhattacharjee, 2001).

The data collection was carried out for two weeks on May 2026 using online Google forms questionnaire. Respondents must answer a screening question, stating that they used a GenAI platform (e.g., ChatGPT, Gemini, Claude) at least once to be included in the study. Respondents were given an informed consent form stating the purpose of the study, prior to beginning the survey. They were told that they were free to choose whether or not to participate, that their responses would not be identified in any way and that the data would only be used for academic purposes. 100 respondents completed the survey successfully and met the analysis criteria. Table 1 shows the background information of the respondents who took part in this study (N = 100).

Table 1. Respondent Profile

	Category	Percentage (%)
Gender	Male	62
	Women	38
Age	20 - 29 years old (gen Z)	27
	30 - 45 years old (gen Y)	67
	46 - 61 years old (gen X)	6
Jobs	Unemployed	2
	Student	16
	Part-Time	3
	Full-Time	74
	Entrepreneur	5
Education	High School/Vocational/Equivalent	3
	D3 (Diploma)	3
	D4/S1 (Bachelor)	77
	S2 (Master)	17
Frequency of GenAI Use	Very Rarely (Less than once a week)	9
	Occasionally (1 - 3 times a week)	10
	Frequently (4 - 6 times a week)	39
	Very Frequent (Daily)	42
GenAI platform used	ChatGPT	75
	Gemini	69
	Claude	26
	Copilot	23
	Others (Dola, Deepseek, Grok, Jenni.AI, Canva AI, Scite AI, Scispace, LM Notebook, Perplexity, Suno, Sora, Supa)	13

Source: Author (2026)

In this study, the Partial Least Squares Structural Equation Modeling (PLS-SEM) was used using the SmartPLS 4 software (Ringle et al., 2024). It was decided to use PLS-SEM, because it is able to test complex models even with relatively small sample size (Hair et al., 2017). A post-hoc power analysis was performed using the G*Power software to check the power of the sample size ($N = 100$). The statistical power was 0.905, given a medium effect size ($f^2 = 0.15$), a significance level (α) of 0.05, and a maximum of 3 predictors directed at the endogenous construct. This value is above the recommended minimum value of 0.80, indicating that the sample size is statistically sufficient and robust enough for the PLS-SEM path estimations.

Items of the questionnaire were modified from previous studies. Each of the statements was evaluated on a 5-point likert scale from 1 (strongly disagree) to 5 (strongly agree). The items of the questionnaire used for each variable are described in Table 2.

Table 2. Items and sources

	Items	Contents	Source
Privacy group (PRIV)	PRIV1	I'm worried that prompts I type into the text box will be used to train generative AI services without my consent.	Ioannou & Tussyadiah (2021)
	PRIV2	I am concerned that generative AI services could make use of my information without my permission.	
	PRIV3	I'm worried about generative AI services being able to access my data without permission.	
	PRIV4	I'm afraid that using generative AI services could lead to the misuse of personal information.	
Perceived risk of AI hallucination (HAL)	HAL1	I doubt the accuracy of the information generated by generative AI.	Lee et al. (2025); Lim et al. (2025)
	HAL2	I think and rethink if AI-generated answers that sound good are true.	
	HAL3	Often I find generative AI information appearing accurate but possibly false.	
Attitude towards using GenAI (ATT)	ATT1	Generative AI is very effective in supporting my self-directed learning activities.	Lim et al. (2025)
	ATT2	Generative AI is incredibly useful to me in learning on my own.	
	ATT3	Generative AI can be a valuable tool to assist in self-directed learning activities.	
Continuance intention (CI)	CI1	I plan on continuing to use generative AI for self-directed learning activities in the future.	Zhou & Ma (2024)
	CI2	I plan to use generative AI to help me with my self-directed learning activities on a regular basis.	
	CI3	I will encourage other people to use generative AI as an aid to self-directed learning activities.	

Source: Author (2026)

4. RESULT AND DISCUSSION

4.1 Result

Table 3 shows that the testing process of the measurement instrument showed good validity and reliability. Convergent validity was achieved, with all indicator items having high factor loadings between 0.715 and 0.961, which is more than the recommended 0.70 by (Hair et al., 2017). In addition, the Average Variance Extracted (AVE) values for PRIV, HAL, ATT and CI were all greater than 0.50, indicating the constructs accounted for more than 50% of the variance in their indicators. In terms of reliability, the Cronbach's Alpha (0.816 – 0.927) and Composite Reliability/CR (0.875 – 0.953) of all the constructs were also found to be greater than the recommended value of 0.70, which means that the research instrument is consistent and free from random error in measurement (Henseler et al., 2015). The outer Variance Inflation Factor (VIF) values ranged from 1.495 to 5.262, which are less than the

acceptable maximum value of 10 (Hair et al., 2018), indicating that there is no critical multicollinearity problem in the measurement model.

Table 3. Measurement Model Assessment

	Items	Loadings	Alpha	CR	AVE	Outer VIF
Privacy concern (PRIV)	PRIV1	0.715	0.902	0.933	0.779	1.495
	PRIV2	0.927				4.152
	PRIV3	0.929				5.262
	PRIV4	0.939				4.783
Perceived risk of AI hallucination (HAL)	HAL1	0.801	0.816	0.875	0.703	1.872
	HAL2	0.961				2.022
	HAL3	0.737				1.654
Attitude towards using GenAI (ATT)	ATT1	0.943	0.927	0.953	0.872	4.018
	ATT2	0.941				4.143
	ATT3	0.918				3.086
Continuance intention (CI)	CI1	0.952	0.896	0.935	0.828	4.911
	CI2	0.951				5.007
	CI3	0.820				1.896

Source: Author (2026)

Fornell-Larcker criterion was used to test for the discriminant validity. The correlation matrix of the key variables is displayed in Table 4. The square roots of all AVE values (from 0.838 to 0.934) were higher than the correlation coefficients, suggesting that the discriminant validity was good (Fornell & Larcker, 1981). To further ensure discriminant validity the Heterotrait-Monotrait (HTMT) ratio of correlations was assessed as reported in Table 5. None of the HTMT values between constructs in the model exceed 0.85, which is the conservative threshold for determining if there is any significant overlap between constructs (Henseler et al., 2015).

Table 4. Discriminant Validity (Fornell-Larcker Criterion)

	PRIV	HAL	ATT	CI
PRIV	0.882			
HAL	0.098	0.838		
ATT	0.106	0.021	0.934	
CI	-0.089	0.141	0.656	0.910

Source: Author (2026)

Table 5. Discriminant Validity (HTMT Ratio)

	PRIV	HAL	ATT	CI
PRIV				
HAL	0.204			
ATT	0.110	0.045		
CI	0.101	0.137	0.702	

Source: Author (2026)

Table 6 also showed the inner VIF values, which were analyzed to see if there is any sign of multicollinearity among the predictor variables. All VIF values are less than 3.0, the maximum recommended value, and are very near to 1.0; this means that collinearity is not a problem in estimating the structural models (Hair et al., 2019).

Table 6. Collinearity Statistics (Inner VIF)

	PRIV	HAL	ATT	CI
PRIV			1.010	1.021
HAL			1.010	1.010
ATT				1.011
CI				

Source: Author (2026)

The R^2 values are the explanatory power of the model. The model on Table 7 accounts for 47.7% of the variance in CI ($R^2 = 0.477$), which is considered moderate. However, weak $R^2 = 0.011$ for ATT shows that PRIV and HAL are not a meaningful explanatory model for the attitudes of the respondents in this study (Hair et al., 2019).

The f^2 effect size reflects the relative contribution of a particular exogenous construct to an endogenous construct (the increase in R^2 when the construct is removed). These values of 0.02, 0.15 and 0.35 denote small, medium and large effects, respectively (Cohen, 1988) (Table 8). The analysis shows that ATT has a very large effect

on CI ($f^2 = 0.852$). However, PRIV and HAL show small effect on CI and no effect on ATT, in line with the non-significant relationships indicated during hypothesis testing.

Table 7. Coefficient of Determination (R^2)

	R^2	Adjusted R^2
ATT	0.011	-0.009
CI	0.477	0.460

Source: Author (2026)

Table 8. Effect Size (f^2)

	f^2	Effect Size
PRIV → ATT	0.011	None
PRIV → CI	0.057	Small
HAL → ATT	0.000	None
HAL → CI	0.039	Small
ATT → CI	0.852	Large

Source: Author (2026)

The bootstrapping procedure with 5000 resamples was used for the significance testing of the structural model to obtain standard errors and T statistics. Results of the hypothesis testing in Table 9, show that only two hypotheses (H2 and H5) are accepted from the hypotheses proposed. The result for H2 showed that PRIV had a significant negative effect on CI as T-statistic = 2.475 at $P < 0.05$ and $P = 0.013$. The t-statistic for H5 was very significant at 9.388 with a P value of 0.000, indicating that ATT is highly significant in improving the CI. On the other hand, hypotheses H1, H3, H4, H6, and H7 were rejected as the P-values of all of them were much larger than 0.05.

For H1, PRIV did not have a significant negative effect on ATT ($T = 0.940$; $P = 0.347$). For H3, HAL had no significant negative impact on ATT ($T = 0.084$; $P = 0.933$). For H4, HAL did not negatively influence CI ($T = 1.313$; $P = 0.189$). For H6, ATT was not proven to mediate the effect of PRIV on CI ($T = 0.910$; $P = 0.363$). For H7, ATT was not proven to mediate the effect of HAL on CI ($T = 0.083$; $P = 0.934$).

Table 9. Hypotheses Testing Results

Hypotheses	Path	β	T statistics	P values	Conclusion
H1	PRIV → ATT	0.105	0.940	0.347	Rejected
H2	PRIV → CI	-0.174	2.475	0.013	Accepted
H3	HAL → ATT	0.011	0.084	0.933	Rejected
H4	HAL → CI	0.144	1.313	0.189	Rejected
H5	ATT → CI	0.672	9.388	0.000	Accepted
H6	PRIV → ATT → CI	0.070	0.910	0.363	Rejected
H7	HAL → ATT → CI	0.007	0.083	0.934	Rejected

Source: Author (2026)

The Standardized Root Mean Square Residual (SRMR) as reported in Table 10 was used to assess the overall model fit. The final results of the estimated model indicated an SRMR of 0.067 and exceeded the 0.080 criterion, indicating a good model fit. Based on variance based SEM (Henseler et al., 2014), the Normed Fit Index (NFI) of 0.861 is a marginal but acceptable fit.

Table 10. Model Fit

	Estimated Model	Threshold	Conclusion
SRMR	0.067	< 0.080	Fit
NFI	0.861	> 0.900	Marginal Fit

Source: Author (2026)

4.2 Discussion

This study's key takeaway strengthens the notion that ATT is a fundamental component of CI in relation to using GenAI technology for self-directed learning activities. GenAI will be a great tool for students to manage their learning pace and needs outside of the classroom. This resonates with the results of research showing that AI qualities significantly shape positive satisfaction and attitudes that in turn drive students' CI to use GenAI in their learning processes (Singh & Paiva, 2025). The results are also aligned with other studies on TAM, which highlight the critical role of affective attitudes and perceived usefulness that emerge from the users themselves in the use of GenAI ATT (Kim & Kim, 2025; Yin et al., 2023). In a practical sense, the universities and training institutions should take care in designing learning activities so that students can feel the benefits of learning. Positive learning experiences can help strengthen positive attitudes and this in turn can increase the chances of long-term adoption.

This study also shows that PRIV has significant impacts on reducing CI for GenAI use. AI can be prompted with certain data, specific learning preferences, or original creations in the self-directed learning environment. As a result, learners are mindful of the advantages of using GenAI for their learning productivity and are concerned about the risk of surrendering control over their privacy. However, high privacy concerns (Shrestha et al., 2024), may hinder CI despite a high ATT for the technology, especially regarding students and youth (Olatunde & Shalan, 2025). This phenomenon aligns with other research showing that users intentionally assess the potential risks of their personal data being exploited before they continue to use a platform (Liang & Shi, 2025; Memarian et al., 2025). Threats to privacy often emerge as negative determinants of the adoption of AI-based technologies, both in developing and advanced countries (Rana et al., 2024). The practical takeaway is that schools and colleges should have clear policies on responsible AI usage and data privacy, and GenAI companies should strive to be more transparent about data practices, such as how data is collected, stored, and used for model training. Stronger privacy mechanisms and more transparent communication around data governance could help to ease misgivings about data and foster continued engagement.

This study has the novel insight that there is no significant impact proven by HAL on both ATT and CI. This indicates that users may already be at a certain level of tolerance or understanding regarding the technical limitations of LLMs. Nowadays, HAL is seen more like a "normal" and acceptable algorithmic irregularity or reasonable error rather than a direct threat that seriously undermines CI (Ariso & Bannister, 2025; Moon, 2024). This too can be better understood if we take into account the level of AI literacy of the respondents, which in turn can affect their perception of HAL. While higher AI literacy does not correspond to greater concern about AI hallucinations, it does indicate a more sophisticated understanding of the limitations of AI (Bewersdorff et al., 2025; Posegga, 2026). Thus, HAL does not reduce their motivation and positive attitude to use GenAI as a learning companion.

These insights highlight the need to address both the technical aspects of minimizing hallucinations and enhancing the users' AI literacy and critical evaluation capabilities to support sustainable GenAI adoption. Policies can be implemented to incorporate AI literacy curricula, which equip learners with tools to verify AI-generated information, evaluate source credibility and identify potential inaccuracies, at universities and training providers. GenAI vendors also need to keep enhancing the reliability of their responses and integrate transparency tools, source citations, and a statement of uncertainty for evaluating the reliability of content generated by AI. These can collectively foster responsible and sustainable applications of GenAI in self-directed learning environments.

5. CONCLUSION

Empirical analysis results support the hypotheses that Positive ATT stimulates CI, and PRIV hinders the use of GenAI by CI. But the hypotheses that the negative effects of HAL can be proved were not proven. Overall, these findings indicate a transformation in user priorities: The sampled postgraduate students and government training attendees are more focused on safeguarding data privacy and transparency in data handling to ensure efficient learning and academic productivity than on issues of potential inaccuracies within AI systems. GenAI seems to be a key tool for independent knowledge acquisition, and AI hallucinations might be seen as minor issues that do not deter further technology adoption.

This study has limitations, with the self-regulated learning abilities and AI literacy of the respondents not yet mapped; this could act as a moderator in explaining why hallucinations are no longer seen as a behavioral threat. It is suggested that the relationship between self-directed learning capabilities, digital literacy and user tolerance of epistemic risks would be worthy of further investigation. Furthermore, future research with larger and more diverse samples, longitudinal designs, moderation analyses of AI literacy and self-regulated learning, and comparisons of various GenAI platforms or learning settings may offer a more holistic view of continuance intention regarding GenAI. From an institutional perspective, the findings indicate that measures to ensure that data are protected should be a priority for educational technology developers and academic institutions, and that users should be given detailed guidelines for using AI in education, supporting safe and effective self-directed learning.

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