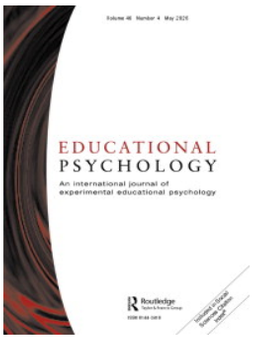

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Making sense of AI feedback: how students' feedback literacy moderates the link between ChatGPT acceptance and self-regulated learning

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ABSTRACT

The integration of generative AI tools like ChatGPT in education raises fundamental questions about boundary conditions where students perceive such technologies as beneficial. This study examines whether students' feedback literacy capabilities determine their perceived educational value from AI interactions. Drawing on the Technology Acceptance Model, we surveyed 211 secondary students (grades 7–9) regarding their ChatGPT acceptance, feedback sense-making abilities, and self-reflection. Hierarchical regression analyses revealed that while technology acceptance components were positively associated with self-reflection, these relationships were consistently moderated by feedback literacy. Specifically, students with stronger feedback sense-making abilities reported greater benefits from ChatGPT use, while those with weaker sense-making skills showed minimal or negative associations. These findings position feedback literacy as a crucial condition influencing perceived educational utility of GenAI tools. The results challenge assumptions about the broad-spectrum or universal benefits of GenAI adoption and highlight the need for targeted and feedback literacy development among learners.

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KEYWORDS
ChatGPT; feedback literacy; feedback sense-making; self-regulated learning

Introduction

ChatGPT has rapidly gained popularity in educational contexts, offering the potential to enhance students' self-regulated learning (SRL) through immediate feedback (Barrot, 2023; Dai et al., 2023; Guo & Wang, 2024; Haleem et al., 2022; Ray, 2023; Su et al., 2023). Understanding how students engage with this technology requires examining their acceptance of and attitudes towards it (Davis, 1989; Sani et al., 2020; Venkatesh & Davis, 2000). The Technology Acceptance Model (TAM) provides a framework for assessing students' acceptance of novel technologies and their integration into learning

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practices (Davis, 1989; Fathema et al., 2015; Tarhini et al., 2017; Teo & Noyes, 2011; Venkatesh & Davis, 2000). Recent studies have applied TAM to investigate students' acceptance of ChatGPT and its influence on SRL strategies (Almogren et al., 2024; Dahri et al., 2024; Lai et al., 2023; Ma et al., 2025; Salloum et al., 2024; Strzelecki, 2024a, 2024b). However, technology effectiveness extends beyond mere acceptance and is often moderated by other variables. As ChatGPT's educational value primarily stems from providing feedback, students' ability to make sense of this feedback, a concept central to feedback literacy (Carless & Boud, 2018), becomes crucial to understand.

Feedback sense-making plays an essential role in both traditional SRL contexts (Carless & Boud, 2018; Dawson et al., 2024; Tai et al., 2018; Yan & Carless, 2022) and GenAI-enabled learning environments (Escalante et al., 2023; McGuire et al., 2024; Steiss et al., 2024). Research on GenAI-enabled SRL presents mixed findings. Some studies report benefits such as reduced cognitive load compared to traditional web searching (Stadler et al., 2024), while others indicate that human expert guidance may better promote metacognition than ChatGPT (Chen et al., 2025). Nevertheless, many studies highlight the benefits of GenAI in enhancing learners' SRL (Lee et al., 2024; Molenaar et al., 2023; Ng et al., 2024; Weng et al., 2024; Wu et al., 2024; Xia et al., 2023). Despite these varied outcomes, research consistently emphasises students' need to critically evaluate AI-generated feedback, suggesting that strong feedback sense-making ability could serve as a significant moderator between ChatGPT use and SRL outcomes.

However, there remains a notable gap in the literature regarding how feedback sense-making moderates the effects of ChatGPT adoption on learners' SRL practices. Informed by the TAM and Zimmerman's SRL theory, this study aims to examine the relationship between secondary school students' acceptance of ChatGPT and their self-reflection as a component of SRL, specifically exploring whether their feedback sense-making ability influences this relationship in a ChatGPT-enabled learning context. Investigating how acceptance of AI-based technologies, moderated by feedback literacy, affects learning outcomes such as self-reflection is both timely and necessary. Despite the growing interest in AI tools like ChatGPT for educational purposes, research exploring these connections is still limited. Current literature primarily focuses on the potential and challenges of such technologies without delving into how students' acceptance and their feedback literacy can moderate the actual impact of AI-based tools (Al-Adwan, 2020; Onah et al., 2021; Zhu et al., 2020). This study examines secondary school students' self-reported perceptions of ChatGPT's educational value and their reported reflective practices.

Educational technology adoption and cognitive processing demands

ChatGPT's rapid adoption in educational contexts reflects both technological optimism and practical necessity (Bettayeb et al., 2024; Zhang et al., 2024). Students increasingly turn to AI systems for assistance with writing, problem-solving, and feedback on their work (Polakova & Ivenz, 2024; Salloum et al., 2024; Shaikh et al., 2023; Strzelecki, 2024a). Yet this adoption outpaces our understanding of when and for whom such tools prove educationally beneficial. The Technology Acceptance Model (TAM; Davis,

1989; Venkatesh & Davis, 2000) provides a framework for understanding adoption patterns, but acceptance alone may be insufficient to predict educational outcomes in contexts where cognitive processing demands are substantial (Weidlich, 2025).

What constitutes a 'GenAI-enabled learning environment' requires careful definition. We conceptualise such environments as educational contexts where generative artificial intelligence systems are integrated to support learning processes through content generation, interaction, and feedback provision. However, unlike traditional educational technologies with transparent algorithms and predictable outputs, GenAI systems operate as 'black boxes' where the reasoning processes, source materials, and reliability mechanisms remain opaque to users (Salih et al., 2025). This opacity creates unique cognitive demands: students must evaluate AI outputs without understanding their provenance or reliability.

The central challenge lies not in the technology itself, but in the cognitive demands it places on users. Unlike traditional educational technologies that present information or facilitate practice, GenAI systems produce novel content that requires evaluation, integration, and strategic application (Ogunleye et al., 2024). Students must determine the accuracy, relevance, and utility of AI-generated responses, capabilities that vary substantially across individuals and developmental stages. This evaluation burden becomes particularly acute in educational settings where AI outputs may appear authoritative but lack pedagogical grounding.

Technology acceptance, self-regulated learning, and feedback literacy

TAM research traditionally focuses on adoption predictors: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitudes (ATT), Intention to Use (ITU), and Actual Use behaviours (AU) (Davis, 1989; Liu et al., 2010; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). PU and PEOU are central to TAM, building on Fishbein and Ajzen (1975) theory of reasoned action, as they shape ATT, ITU, and AU (Cakır & Solak, 2015; Chintalapati & Daruri, 2017; Tarhini et al., 2017; Teo & Noyes, 2011). These components effectively predict technology uptake but may inadequately capture the cognitive processes required for effective educational use (Barz et al., 2024).

According to Davis (1989), PU refers to 'the degree to which a person believes that using a particular system would enhance their job performance', while PEOU refers to 'the degree to which a person believes that using a particular system would be free from effort'. In our study context, PU is operationalised as the degree to which learners believe ChatGPT will enhance their learning performance, and PEOU as the degree to which they believe ChatGPT is easy to use in learning practices. ATT represents learners' positive or negative feelings about using ChatGPT (Davis, 1989), ITU refers to their plans to use ChatGPT in the future, and AU captures self-reported frequency and duration of ChatGPT use. The TAM framework posits that learners' perceptions of usefulness and ease of use shape their attitudes towards ChatGPT, which subsequently influence their intention to use it and their actual utilisation patterns (Cakır & Solak, 2015; Davis, 1989; Kamal et al., 2020; Tarhini et al., 2017; Teo & Noyes, 2011). Recent extensions of TAM in educational contexts have begun incorporating SRL components, showing that the relationship between acceptance and

learning outcomes depends on individual processing capabilities (An et al., 2024; Stöckl, 2025).

When AI systems generate responses that students must evaluate and integrate, the relationship between acceptance and learning outcomes becomes contingent on individual processing capabilities. SRL theory provides insight into these cognitive processes. Zimmerman's (2002) cyclical model emphasises self-reflection as the phase where students evaluate performance and adjust strategies based on feedback. In this phase, when students evaluate their performance and refine strategies for upcoming tasks, AI systems enable students to seek timely, personalised feedback to enhance their self-evaluation and modify learning strategies accordingly (Lee et al., 2024; Molenaar et al., 2023; Weng et al., 2024). This capacity pertains to students' ability to self-assess. Self-assessment plays a vital role in this phase, helping students conduct self-directed feedback-seeking and performance evaluation (Yan, 2020; Yan and Mendoza, 2025). Through AI-generated feedback, students can promptly self-assess their learning performance, seeking feedback and suggestions that help them critically evaluate their learning strategies. This process enables informed adjustments to their approaches, enhancing their overall educational experience and promoting a deeper understanding of their learning journey. However, this rests on the assumption that students can effectively interpret and utilise feedback information, which is an assumption that may not hold when feedback comes from AI systems (Junaštíková, 2024).

Hence, students' capacity to interpret, evaluate, and strategically use information intended to guide learning is crucial to bridge technology acceptance and SRL. This capacity is often referred to as feedback literacy (Carless & Boud, 2018; Dawson et al., 2024). Feedback literacy is an essential capability emphasising learners' active role in constructing meaning from information to facilitate SRL outcomes (Boud & Molloy, 2013; Carless, 2015; Han & Xu, 2020; Yan & Brown, 2017; Yan & Carless, 2022). The concept, first introduced by Sutton (2012) as the ability to read, interpret, and use feedback, was expanded by Carless and Boud (2018) to encompass 'understandings, capacities, and dispositions needed to make sense of information and use it to enhance work or learning strategies' (p.1316). Key processes involve interpreting, evaluating, and integrating external feedback to guide improvement (Carless & Boud, 2018; Nicol & Macfarlane-Dick, 2006). These processes include appreciating feedback, making judgments, managing affect, and taking action, along with skills like seeking clarification, determining source credibility, and relating comments to standards (Boud et al., 2013, 2015; Molloy et al., 2020; Tai et al., 2018). Studies emphasise that the ability to make sense of feedback information is particularly crucial for enabling the downstream benefits of SRL (Dawson et al., 2024; Tai et al., 2018). This ability becomes particularly crucial when interacting with AI systems that produce responses without accounting for individual learning contexts, prior knowledge, or specific educational objectives, unless otherwise stated.

AI-generated content as educational feedback: theoretical considerations

Students increasingly treat ChatGPT outputs as feedback-like information, though these responses may not meet technical definitions of educational feedback (Winstone & Carless, 2020). Effective educational feedback typically exhibits several characteristics:

specificity to individual performance, alignment with explicit learning goals, actionability that guides improvement efforts, and timing that supports learning processes (Carless & Boud, 2018). AI-generated responses frequently lack these characteristics, operating without knowledge of individual student contexts, learning objectives, or performance standards. Although AI-generated feedback can positively influence learning outcomes (Cunningham, 2019; Pardo et al., 2019; Wood, 2022), these benefits may be limited if students lack the critical skills to make sense of such feedback.

The gap between student perceptions and feedback reality creates a critical challenge. Meyer et al. (2024) demonstrated that while AI-generated feedback can motivate students and support text revision, its effectiveness depends heavily on students' ability to evaluate and integrate the suggestions appropriately. Students may perceive ChatGPT responses as helpful feedback when the content is actually generic, inaccurate, or misaligned with their learning needs. This perception-reality gap suggests that students' metacognitive capabilities for evaluating feedback quality become more important than the objective characteristics of the information provided.

Furthermore, the conversational nature of ChatGPT interactions may create an illusion of personalised attention that masks the system's fundamental limitations. Unlike human feedback providers who can observe student performance, understand individual learning trajectories, and adjust responses based on context, AI systems generate responses through pattern matching without genuine understanding of student needs (Weidlich, 2025). This creates particular risks for students who lack the evaluative skills to distinguish between superficially helpful and genuinely educational responses.

The present study

This study examines whether feedback literacy moderates the relationship between ChatGPT acceptance and SRL among secondary school students. We hypothesise that students with stronger feedback sense-making abilities will show positive associations between technology acceptance and self-reflection, while those with weaker capabilities will show minimal or potentially negative relationships. This pattern would position feedback literacy as a boundary condition determining when AI adoption translates into perceived learning benefits (see Figure 1). This study had two main hypotheses:

1. The five components of ChatGPT acceptance (i.e., perceived usefulness, perceived ease of use, attitude, intention to use, and actual use) will have a positive and significant relationship with self-reflection while controlling for demographic factors. Specifically, we test whether perceived usefulness (PU; H1.1), perceived ease of use (PEOU; H1.2), attitude (ATT; H1.3), intention to use (ITU; H1.4), and actual use (AU; H1.5) will positively predict self-reflection.
2. Feedback sense-making will moderate the positive relationships between ChatGPT acceptance components and self-reflection while controlling for demographics. Specifically, we test the interactions between feedback sense-making and PU (H2.1), PEOU (H2.2), ATT (H2.3), ITU (H2.4), and AU (H2.5) in predicting self-reflection.

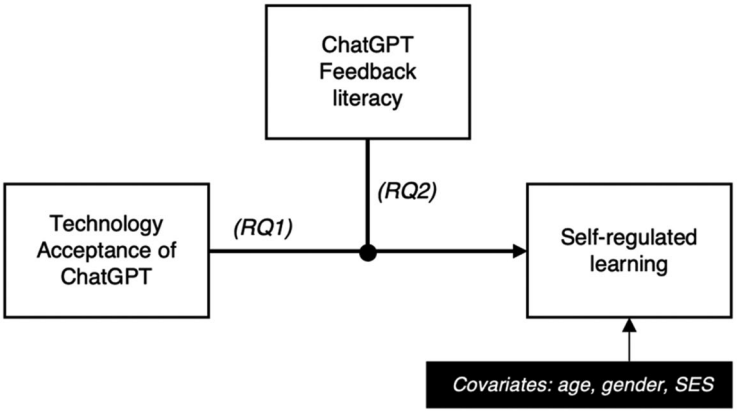

Figure 1. The moderating role of making sense of feedback on the link between ChatGPT technology acceptance and self-regulated learning.

Methods

Participants and procedures

A total of 220 students initially participated. After excluding nine cases with suspicious response patterns, 211 students (Grades 7–9) from a government-funded secondary school in Hong Kong SAR that recently implemented AI literacy initiatives were included in the analysis. The sample included 102 Grade 7, 49 Grade 8, and 60 Grade 9 students, with balanced gender representation (51% female). This developmental range (ages 12–15) captures a critical period for metacognitive skill development and technology adoption patterns (Weil et al., 2013).

The data collection was conducted in October 2023 through an online survey platform (Qualtrics; e.g., Mendoza et al., 2023). The second author went to the school in person, sent out the survey link via students' school email addresses, and stood by for support. The survey was taken before a Chinese course for each grade. Chinese course teachers in each classroom facilitated to remind students to check their school email accounts to find the survey link and leave 10 minutes for students to fill out the survey. The study was approved by the Human Research Ethics Committee of the affiliated university of all authors. Then, the study was approved by the local school principal, and information consent sheets were distributed to students and their parents/guardians in late September 2023, while the online survey was prepared to send out for review. The surveys were developed in traditional Chinese and were proofread by local scholars and the contact teacher in the local school.

Measures

Technology acceptance of ChatGPT

ChatGPT Technology Acceptance was measured using a 25-item instrument adapted from Davis (1989) through systematic simplification for adolescent comprehension. Following cognitive interviews with 15 students, items were refined to ensure clarity while maintaining construct validity (DeVellis & Thorpe, 2021). The final scale assessed

PU (α=.92), PEOU (α=.90), ATT (α=.92), ITU (α=.93), and self-reported usage (AU) frequency (α=.95). The first four subscales used a 6-point Likert scale (1 = Strongly Disagree to 6 = Strongly Agree), while AU employed a frequency scale (1 = Never to 6 = Very Frequent). Sample items include: 'ChatGPT can improve my learning performance' (PU); 'Learning to use ChatGPT is easy for me' (PEOU); 'I find learning with ChatGPT to be interesting and fun' (ATT); 'I plan to use ChatGPT for my future schoolwork' (ITU); and 'How frequently have you used ChatGPT for your assignments or homework?' (AU). Confirmatory factor analysis supported the five-factor structure (CFI=.941, TLI=.922, RMSEA=.064), with all items loading significantly on their intended factors.

Feedback sense-making

Feedback Sense-Making used the 4-item Making Sense of Feedback subscale from Dawson et al. (2024) Feedback Literacy Behaviour Scale, adapted to reference ChatGPT interactions. Items assessed students' reported evaluation of AI-generated information credibility and utility (α=.94). Responses are provided on a 6-point frequency scale (1 = never, 6 = always). A sample item is 'I carefully consider comments from ChatGPT about my learning performance before deciding whether to adopt them' Table 1 provides the items used and the construct-dimension-item mapping demonstrating that these items capture evaluative processing, beyond learning dispositions. Sample

Table 1. Construct-Dimension-Item mapping for feedback sense-making scale.

MSF item	Dimension	Original item (Dawson et al., 2024)	Adapted item (ChatGPT context)	Adaptation
1	Decision to use	"I carefully consider feedback comments about my work before deciding if I will use them or not"	"I carefully consider comments from ChatGPT about my learning performance before deciding whether to adopt them"	Specified ChatGPT as feedback source
2	Judgement of conflicting information	"When receiving conflicting feedback about my work from different sources, I make a judgment about what I will use"	"When receiving conflicting comments from ChatGPT about my learning performance, I make my own judgment about which comments to adopt"	Adapted to ChatGPT context; retained judgement focus
3	Credibility assessment	"When deciding what to do with feedback comments, I consider the credibility of their sources"	"I consider the credibility of ChatGPT's comments about my learning performance before deciding how to use them"	Specified ChatGPT source; retained credibility evaluation
4	Standards alignment	"I consider how feedback relates to criteria or standards"	"I think about the relationship between ChatGPT's comments and the evaluation criteria or standards"	Contextualized to ChatGPT feedback

Note: All items adapted from the Making Sense of Feedback subscale (Dawson et al., 2024) to reference ChatGPT-generated feedback. Items measure evaluative processing (credibility assessment, decision-making, judgement) rather than broader learning dispositions. Scale reliability: α = .94.

items include 'I carefully consider comments from ChatGPT about my work before deciding if I will use them or not' and 'When deciding what to do with ChatGPT comments, I consider the credibility of their sources'.

Self-reflection measuring self-regulated learning (SRL)

SRL was measured using Yan's (2018) Self-assessment Practice Scale, particularly the 7-item self-reflection subscale, capturing students' reported engagement in reflective learning practices (α=.93). This introspective practice, supported by both internal and external feedback, allows students to identify their strengths and weaknesses, thus playing a crucial role in SRL, specifically within the self-reflection phase (see Mendoza and Yan, 2021; Mendoza et al., 2023). Rated on a 6-point Likert scale, it includes items like 'I seek out the reasons for mistakes I made after getting back marked work' and 'I think about whether the way I am studying is really helping me learn'.

Data analysis

Nine participants were excluded from the data analysis for suspicious response patterns and outlier analyses based on Mahalanobis distances. With 211 participants and a maximum of seven predictors included in any one model, our sample exceeds the commonly recommended minimum ratio of 15–20 participants per predictor (Green, 1991; Tabachnick & Fidell, 2013). Using G*Power (Faul et al., 2009), we confirmed that this sample size provides over 90% power to detect medium effect sizes ($f2 = 0.15$) at $\alpha = 0.05$ in hierarchical regression analyses.

Prior to analysis, we rigorously tested all relevant assumptions for hierarchical multiple regression. Linearity was assessed through scatterplots and partial regression plots between each predictor and self-reflection, which showed no evidence of non-linear relationships. The normality of residuals was confirmed through visual inspection of Q-Q plots and non-significant Shapiro-Wilk tests (p>.05) for each model. For multicollinearity assessment, we examined variance inflation factors (VIFs) for all predictors. While the correlation between intention to use and attitude towards ChatGPT was high (r=.83), VIF values remained below 3.5 across all predictors, well under even conservative thresholds of 5.

Hierarchical multiple regression analyses were conducted using R to examine the study hypotheses. In Step 1 of the regression models, age, gender, and socioeconomic status were entered as demographic control variables. The selection of these control variables was based on established evidence of their associations with both technology acceptance (Venkatesh et al., 2003) and SRL (Panadero, 2017; Pintrich, 2004; Pintrich & Zusho, 2002; Zimmerman, 2000). These variables have been identified as potential confounders in educational technology research, as they may influence both predictor and outcome variables independently of the relationships under investigation. In Step 2, the predictor variables of interest were entered: PU, PEOU, ATT, ITU, and AU of ChatGPT. In Step 3, the moderator of making sense of feedback was entered along with the interaction term between the predictor and moderator.

A total of 5 sets of regression models were tested to examine the relationship between each ChatGPT acceptance component and self-reflection and whether making

sense of feedback moderated these links. PU was the predictor in Model 1, PEOU in Model 2, ATT in Model 3, ITU in Model 4, and AU in Model 5. The Johnson-Neyman technique was used to identify values along the range of the moderator at which the effect of the predictor on the outcome transitions between statistically significant and nonsignificant (e.g., Mendoza and Yan, 2023). Simple slope analyses plotting the interactions at low (−1 SD), moderate (mean), and high (+1 SD) values of the moderator were also conducted. All continuous variables were mean-centred and scaled by one standard deviation prior to analysis.

Results

Table 2 presents descriptive statistics and intercorrelations among study variables. All constructs demonstrated positive zero-order correlations and normal distributions, with means consistently above scale midpoints. Hierarchical regression analyses examined whether feedback sense-making moderated associations between ChatGPT acceptance components and self-reported reflection. Each analysis followed a systematic three-step approach: demographic controls, main effects, and interaction terms. Given space constraints and conceptual similarity across models, we present integrated results focusing on moderation patterns while providing complete model statistics in Supplementary Materials (see Table 3).

Consistent with Hypothesis 1, all five TAM components, PU (β=.40, $p < .001$), PEOU (β=.45, $p < .001$), ATT (β=.39, $p < .001$), ITU (β=.30, $p < .001$), and AU (β=.27, $p < .001$), significantly predicted self-reflection when added after the control variables. These results suggest that higher levels of ChatGPT acceptance are associated with greater self-reflection, controlling for student demographics.

Supporting Hypothesis 2, making sense of feedback significantly moderated the relationship between each TAM component and self-reflection. In all final models, the interaction terms between each TAM variable and feedback sense-making were statistically significant (βs ranged from .11 to .20, ps < .05), and the overall models

Table 2. Intercorrelations and descriptive statistics.

	1	2	3	4	5	6	7
1. Perceived Usefulness	(0.92)						
2. Ease of Use	0.682***	(0.90)					
3. Attitude	0.786***	0.737***	(0.92)				
4. Intention	0.720***	0.635***	0.825***	(0.93)			
5. Actual Use	0.506***	0.466***	0.565***	0.620***	(0.95)		
6. Make Sense of Feedback	0.601***	0.597***	0.569***	0.581***	0.529***	(0.94)	
7. Self-Reflection	0.409***	0.446***	0.386***	0.313***	0.276***	0.501***	(0.93)
Mean	4.35	4.40	4.28	4.10	3.32	4.21	4.31
SD	0.99	0.98	1.04	1.08	1.21	1.00	0.85
Skewness	−0.45	−0.06	−0.01	−0.24	−0.22	−0.23	0.05
Kurtosis	1.23	−0.14	−0.22	0.58	−0.57	0.73	0.92

Note. Values shown in parentheses on the diagonal are internal consistency reliabilities of the scales (Cronbach's alpha).
***$p < 0.001$.
**$p < 0.01$.
*$p < 0.05$.

Table 3. Summary of hierarchical regression results: predicting self-reflection from ChatGPT acceptance and feedback sense-making.

Predictor	Model 1 (PU)	Model 2 (PEOU)	Model 3 (ATT)	Model 4 (ITU)	Model 5 (AU)
Step 1: Controls					
Grade	0.029	0.064	0.036	0.034	0.052
Gender	0.150	0.188	0.215	0.181	0.169
SES	−0.049	−0.045	−0.047	−0.058	−0.059
Step 2: Main effect					
TAM Component	0.182*	0.254***	0.131	−0.013	−0.008
Step 3: Moderation					
Feedback Sense-Making (MSF)	0.407***	0.364***	0.455***	0.550***	0.533***
Interaction (TAM × MSF)	0.111*	0.160***	0.178***	0.201***	0.117*
Model summary					
R^2	.299	.342	.331	.342	.284
Adjusted R^2	.280	.320	.310	.320	.260
ΔR^2 from Step 2	.125	.124	.168	.234	.197
$F(6, 204)$	14.49***	17.66***	16.85***	17.69***	13.50***

Note: PU = Perceived Usefulness, PEOU = Perceived Ease of Use, ATT = Attitude, ITU = Intention to Use, AU = Actual Use. All values are standardised β coefficients from the final model (Step 3).

*$p < .05$.

**$p < .01$.

***$p < .001$.

Johnson-Neyman Threshold Values: PU: Effect significant when MSF > 3.89; EOU: Effect significant when MSF > 3.55; ATT: Effect significant when MSF < 2.13 or MSF > 4.26; INT: Effect significant when MSF < 3.49 or MSF > 5.01; USE: Effect significant when MSF < 2.00.

explained substantial variance in self-reflection (R^2=.28 to .34; see Supplementary Tables 1–5). Specifically, the interaction between PU and feedback sense-making was significant (β=.11, p=.02).

Johnson-Neyman analyses revealed that technology acceptance components were associated with self-reported reflection only at moderate-to-high levels of feedback sense-making. For PU, significant associations emerged when students' feedback sense-making scores were above 3.89 (see Figure 2a). Simple slope analyses showed that this relationship was significant at high levels of feedback sense-making (β=.25, $p < .01$) and moderate levels (β=.16, p=.02), but non-significant at low levels (β=.06, p=.39; see Figure 2b). A similar pattern emerged for PEOU, with a significant interaction (β=.16, $p < .001$) and a threshold of 3.55 (Figure 2c). Simple slopes indicated that PEOU predicted self-reflection at moderate (β=.22, $p < .01$) and high levels (β=.36, $p < .01$) of feedback sense-making, but not at low levels (β=.08, p=.24) (Figure 2d).

The interaction between ATT towards ChatGPT and feedback sense-making was also significant (β=.18, $p < .001$), with the relationship emerging only at high levels of the moderator (above 4.26, Figure 2e). At low levels of sense-making, the relationship between ATT and self-reflection was not significant (β=-.04, p=.59); at moderate levels, it approached significance (β=.11, p=.07); however, at high levels, it became strong and positive (β=.25, $p < .01$) (Figure 2f). In contrast, the moderation effect for ITU showed a more nuanced pattern. While the interaction was significant (β=.20, $p < .001$), Johnson-Neyman analysis revealed that the relationship was significant when feedback sense-making was either below 3.49 or above 5.01 (Figure 2g). Simple slope analysis indicated a negative relationship at low feedback sense-making (β=-.17, p=.01), no significant relationship at moderate levels (β=-.01, p=.86), and a positive relationship at high levels (β=.15, p=.02) (Figure 2h), suggesting a crossover interaction where students with low sense-making may misapply or over-rely on their intended use of ChatGPT.

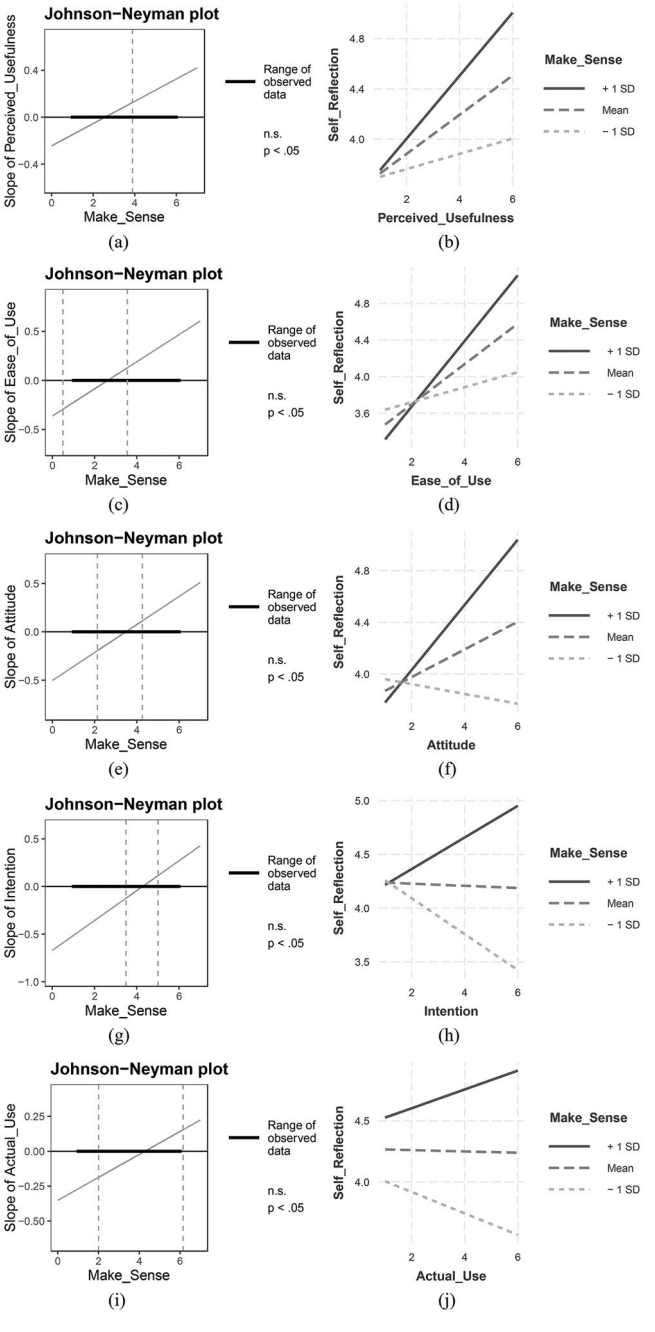

Figure 2. Moderation effects of making sense of feedback on the relationship between ChatGPT acceptance and self-reflection.

Note: Johnson-Neyman plots (panels a, c, e, g, i) show regions where the relationship between each ChatGPT acceptance components and self-reflection is statistically significant ($p < .05$, blue shading) versus non-significant (red). Black vertical lines indicate the range of observed data. Simple slopes plots (panels b, d, f, h, j) illustrate how these relationships change at different levels of Make_Sense (MSF): low (−1SD = 3.21), moderate (mean = 4.21), and high (+1SD = 5.21). For Perceived Usefulness (panels a-b) and Ease of Use (panels c and d), significant effects emerge at moderate-to-high MSF levels within the observed range. For Attitude (panels e and f) and Intention (panels g-h), effects show antagonistic iteraction effect where relationships shift from negative to positive as MSF increases. For Actual Use (panels i and j), the significant region falls almost entirely outside the observed data range, indicating limited practical moderation within typical student capabilities.

Lastly, the interaction between AU and feedback sense-making was statistically significant (β = .12, p = .02), though the pattern requires careful interpretation. Johnson-Neyman analysis indicated that the relationship between actual use and self-reflection was statistically significant only when feedback sense-making scores were below 2.00 (Figure 2i). However, this threshold falls well outside the practical range of our observed data (M = 4.21, SD = 1.00), representing an extremely low level of feedback sense-making more than two standard deviations below the sample mean. Simple slope analyses confirmed that none of the slopes at low (β=-.09, p=.17), moderate (β=-.01, p=.92), or high (β=.08, p=.18) levels within the typical range of observed capabilities reached statistical significance (Figure 2j).

This suggests that within the practically meaningful range of feedback sense-making capabilities observed in our sample, actual ChatGPT use shows no clear conditional relationship with self-reflection. The significant interaction term appears driven primarily by extreme low values rarely observed in secondary school populations with AI literacy initiatives. Unlike the other TAM components where moderation effects operated within typical ranges of student capabilities, the link between actual use and self-reflection does not appear reliably contingent on feedback sense-making among students with even minimally developed evaluative skills.

Discussion

This study examined the relationship between students' acceptance of ChatGPT and SRL, with a particular focus on the moderating role of feedback sense-making. Our results supported both hypotheses, revealing a nuanced interplay between various components of technology acceptance and self-reflection, contingent on students' ability to make sense of feedback.

Interpreting main effects

The positive associations between all five components of ChatGPT acceptance and self-reported reflection (H1) provide empirical support for extending the TAM to AI-enabled learning contexts. These findings align with established TAM research demonstrating how user perceptions relate to technology adoption patterns in educational settings (Barak, 2010; Bazelais et al., 2018; Tarhini et al., 2017; Teo & Noyes, 2011; Waheed & Jam, 2010), and specifically with recent studies examining ChatGPT acceptance in educational contexts (Almogren et al., 2024; An et al., 2024; Barz et al., 2024; Dahri et al., 2024; Sallam et al., 2023; Strzelecki, 2024a, 2024b)

Our findings extend established TAM principles to the specific context of AI-based feedback tools among secondary students, who received limited attention compared to the extensive higher education research in this area (Bettayeb et al., 2024; Zhang et al., 2024). The strength of association between TAM components and self-reflection varied meaningfully, with PEOU (β=.45) and PU (β=.40) showing stronger relationships than ATT (β=.39), ITU (β=.30), and AU (β=.27). This pattern suggests that students' beliefs about ChatGPT's utility and usability may be more influential for self-reported

reflection than their affective responses or behavioural engagement, aligning with findings from Salloum et al. (2024), Lai et al. (2023), and Ma et al. (2025) that perceived usefulness and ease of use consistently emerge as primary drivers of GenAI tool adoption among students across diverse educational contexts.

These results provide tentative support for conceptual predictions that GenAI tools could enhance students' self-assessment and metacognitive capabilities (Barrot, 2023, 2024; Dai et al., 2023; Ng et al., 2024; Weng et al., 2024; Wu et al., 2024). As Molenaar et al. (2023) observed, AI tools like ChatGPT can provide immediate personalised feedback that may facilitate the self-reflection phase of SRL when students perceive the technology as useful and accessible. The consistent positive associations across all TAM components offer preliminary empirical evidence for theoretical claims about ChatGPT's potential to support self-directed feedback-seeking and performance evaluation, as described in our theoretical framework.

However, these associations should be interpreted with considerable caution, as they reflect student perceptions of their self-regulatory experiences rather than observed learning behaviours or objectively measured outcomes. The relationships we identify suggest how students with varying technology acceptance report different experiences with self-reflection, but do not establish that ChatGPT use causally improves metacognitive capabilities or learning performance. This distinction becomes particularly important given the perception-reality gap we identified in our theoretical analysis of AI-generated content as educational feedback.

The moderating role of feedback sense-making

Our second hypothesis regarding the moderating effect of feedback sense-making was strongly supported across all TAM components, indicating that the associations between ChatGPT acceptance and self-reflection are significantly influenced by students' ability to critically process and evaluate AI-generated information. This finding represents a contribution to understanding the boundary conditions determining AI tools' perceived educational utility, directly addressing the notable gap in literature regarding how feedback literacy moderates AI adoption effects on SRL practices (Al-Adwan, 2020; Onah et al., 2021; Zhu et al., 2020).

The moderation patterns directly address the theoretical challenge we identified regarding students' need to evaluate AI outputs without understanding their provenance or reliability. For PU and PEOU, associations with self-reflection were significant only at moderate-to-high levels of feedback sense-making. This suggests that students may derive perceived self-regulatory benefits from finding ChatGPT useful and accessible primarily when they possess cognitive abilities to critically evaluate the information it provides; these are capabilities that appear essential given the 'black box' nature of GenAI systems we described.

This pattern shows consistency with emerging research demonstrating that students' evaluative capabilities influence their ability to distinguish helpful from unhelpful AI-generated content (Albayati, 2024; Escalante et al., 2023; McGuire et al., 2024; Meyer et al., 2024; Steiss et al., 2024). The finding extends recent work by Barz et al. (2024) and An et al. (2024), which found that SRL capabilities moderate technology

acceptance relationships in e-learning contexts (Bai et al., 2022; Lau & Jong, 2022), by suggesting that feedback processing skouills serve as equally important moderators in AI-specific contexts. These results provide preliminary empirical support for the theoretical assertion that students' capacity to interpret, evaluate, and strategically use AI-generated information may represent a critical bridge between technology acceptance and SRL.

The moderating effect for attitude towards ChatGPT revealed a more pronounced pattern, with positive associations emerging primarily at high levels of feedback sense-making. This suggests that positive predispositions towards ChatGPT may translate into perceived self-regulatory benefits, mainly when students can effectively distinguish valuable information from less useful responses, which appears crucial given our theoretical analysis showing how the conversational nature of ChatGPT may create illusions of personalised attention that mask fundamental system limitations.

The complex moderation pattern for intention to use ChatGPT, where associations with self-reflection were negative at low feedback sense-making levels but positive at high levels, provides preliminary empirical evidence for a theoretical distinction between problematic dependency and strategic resource utilisation. Students with weaker feedback evaluation abilities who express strong intentions to use ChatGPT may be indicating overreliance rather than strategic learning behaviour (Lipnevich & Panadero, 2021), while students with stronger feedback literacy appear to approach the technology as one resource among many.

This interaction offers initial support for understanding when AI adoption may be counterproductive, aligning with concerns raised by Weidlich (2025) and Stadler et al. (2024) about the need for critical evaluation skills in AI-mediated learning environments. Students lacking the ability to distinguish between superficially helpful and genuinely educational responses may potentially develop dependency patterns, though our cross-sectional design prevents us from establishing whether such patterns actually develop over time or affect learning outcomes.

The implications may extend beyond individual differences to considerations of developmental readiness for AI tool engagement. Given that our sample spans grades 7–9, these moderation effects could reflect not only individual differences in cognitive capabilities but also developmental variations in metacognitive skills across this age range, though our study design limits our ability to examine these developmental patterns systematically.

Theoretical and practical implications

Collectively, our findings suggest feedback sense-making as a potentially important boundary condition for realising perceived educational benefits from AI tools like ChatGPT. The substantial proportion of variance in self-reflection explained by the interaction terms (ΔR^2 ranging from .124 to .234) indicates that individual differences in feedback processing capabilities may represent a major source of variation in AI-mediated learning experiences, though the cross-sectional nature of our study limits causal interpretations of these relationships.

These results suggest potential extensions to TAM theory by indicating that acceptance-outcome relationships may depend on individual sense-making abilities,

which has received limited attention in traditional TAM research (Davis, 1989; Venkatesh & Davis, 2000). Our findings may contribute to feedback literacy theory by suggesting how the abilities to appreciate feedback, make judgments about its value, and take action based on feedback (Carless & Boud, 2018) could be equally important when feedback comes from artificial intelligence systems. The consistent moderation patterns across TAM components suggest that feedback sense-making may represent a fundamental cognitive prerequisite for productive AI engagement, supporting our theoretical positioning that this capability bridges technology acceptance and self-regulated learning.

The varied moderation patterns across TAM components also contribute to understanding the complexity of technology-learning relationships. The finding that different acceptance components interact differently with feedback literacy (from amplification effects for usefulness and ease of use to crossover interactions for intention) suggests that individual difference variables may create complex conditional relationships rather than simple additive effects. This complexity aligns with our theoretical analysis showing that the evaluation burden becomes particularly acute in educational settings where AI outputs may appear authoritative but lack pedagogical grounding.

In terms of educational practice, our findings suggest several potential strategies for AI integration in secondary education contexts, though these recommendations should be considered preliminary given our study's methodological constraints. Educational institutions may benefit from prioritising feedback literacy development alongside AI tool implementation, addressing the cognitive processing demands we identified as central challenges in GenAI-enabled learning environments.

Based on our moderation findings, we recommend a three-tier implementation framework. For Tier 1, all students may benefit from: explicit instruction in evaluating AI credibility; weekly practice sessions comparing AI responses to expert feedback on identical tasks; metacognitive prompting strategies embedded in assignments: 'How do I know this AI response is helpful?' or 'What would I need to verify before using this suggestion?'; and/or regular reflection activities on AI interaction experiences. Tier 2, for students with moderate feedback literacy, scaffolded AI interaction may be provided by: structured AI prompting templates that require students to specify learning goals before prompting; peer collaboration protocols where students compare and evaluate AI responses together; teacher-mediated reflection sessions following AI interactions; and/or guided practice in identifying when AI responses are generic, inaccurate, or misaligned with learning needs. Finally, for Tier 3, for students with high feedback literacy, independent AI use can be facilitate through: access to advanced AI tools with minimal restrictions; advanced projects examining AI response quality across domains; and/or mentorship responsibilities for students developing feedback literacy skills.

Relatedly, schools can consider using the Feedback Sense-Making subscale from the Feedback Literacy Behaviour Scale (Dawson et al., 2024) to determine appropriate tier placement. Based on our Johnson-Neyman analysis, a threshold score of 4.2 (on a 1–6 scale) distinguishes students who report benefiting from ChatGPT acceptance from those who do not. We recommend quarterly reassessment to identify students ready for tier advancement, recognising that feedback literacy can be developed through targeted instruction.

Further, the interaction effects we observed for intention to use provides preliminary guidance for identifying students who may require intervention. Students who express strong acceptance for AI tools (high intention to use) but demonstrate limited critical evaluation skills (low feedback sense-making) may be at risk for problematic dependency patterns. Teachers need preparation that extends beyond technical training to include understanding of feedback literacy principles and recognition of students who may be struggling with AI interactions despite expressing positive attitudes.

Rather than universal AI adoption policies, our findings suggest institutions should consider differentiated approaches based on individual feedback literacy capabilities rather than grade level alone. Our preliminary developmental analysis suggests that chronological age may be less predictive than individual differences in metacognitive readiness. This framework provides actionable guidance while acknowledging that empirical validation through intervention studies is needed to establish effectiveness.

Limitations and directions for future research

Several important limitations constrain interpretation of our findings and point towards critical directions for future research. The cross-sectional design prevents causal inference; we observe associations between student perceptions at a single time point rather than demonstrating that feedback literacy moderates differential technology effects over time. This limitation is particularly problematic when examining developmental phenomena in early adolescence, where metacognitive capabilities are rapidly evolving. Longitudinal designs are needed to establish whether feedback literacy development actually improves students' ability to benefit from AI interactions, or whether students with stronger baseline capabilities simply report more positive experiences.

The reliance on self-report measures means findings reflect student perceptions rather than observed behaviours or objective learning outcomes. Students' reported reflection capabilities may not align with actual metacognitive practices, and their perceptions of ChatGPT's utility may differ substantially from objective learning assessments or expert evaluations of learning quality. Future research should incorporate behavioural observations, performance measures, or analyses of actual AI interaction patterns to provide more robust evidence than perceptual measures alone.

Our measurement of feedback sense-making, while adapted from established instruments, focuses on students' reported evaluation behaviours rather than their actual capacity to distinguish high-quality from low-quality AI feedback. Recent work by Meyer et al. (2024) demonstrates the value of incorporating performance-based assessments in AI feedback research, approaches that would strengthen evidence beyond our current methodology.

The focus on secondary students in a single educational system limits generalisability across contexts and cultures, while our developmental range (grades 7–9) encompasses substantial variation in metacognitive capabilities that our cross-sectional design prevented us from examining systematically. Future research should investigate whether the moderation patterns we observe differ across grade levels, with particular attention to whether younger students require different support structures for productive AI engagement than older students within this developmental window.

Additionally, our study was conducted during a specific period of ChatGPT adoption (October 2023) when the technology was relatively novel and media coverage was predominantly positive. Students' perceptions and acceptance patterns may differ as AI tools become more routine and awareness of their limitations increases. The high means we observed across all measures may reflect early adoption enthusiasm rather than stable relationships that would persist over time.

Future research should address these limitations through experimental or longitudinal designs that can establish temporal relationships and test whether feedback literacy interventions improve AI interaction outcomes. Multi-method approaches incorporating objective performance measures, analysis of actual AI interactions, and systematic examination of developmental differences would substantially strengthen our understanding of when and how AI tools can effectively support SRL in educational contexts.

Conclusion

Our findings situate feedback literacy as a crucial student capacity in AI-enhanced education, revealing it as a critical boundary condition for realising the perceived learning benefits of AI tools like ChatGPT. Rather than technical capabilities, students' ability to actively process AI-generated feedback appears to determine its reported impact on SRL outcomes. This aligns with the conceptual shift recognising learners as active agents in feedback processes (Carless & Boud, 2018; Nieminen & Carless, 2023; Tai et al., 2018). While ChatGPT is often tagged as a 'game changer', our results suggest that its benefits still depend on the *player*. Our results indicate a potential shift from technology-centered to literacy-centered approaches, reframing educational AI discourse from 'which tools to implement' towards 'which cognitive capacities to develop'. As AI tools continue to evolve and become normalised, developing students' ability to critically process AI-generated feedback may ultimately influence whether technological advancement translates to meaningful educational outcomes. The future of AI in education may depend less on algorithmic complexity and more on human capabilities to meaningfully engage with information drawn from artificial intelligence.

Disclosure statement

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