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Understanding Behavioral Intention to Use AI Note-Taking Tools in Online Learning: A Self-Determination Theory Perspective

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Abstract

With the rapid development of artificial intelligence (AI), AI note-taking has become an important learning support tool for knowledge integration and thinking development, yet it is still mainly viewed as an efficiency-enhancing supplement to traditional note-taking. Therefore, understanding the factors associated with learners' behavioral intention (BI) to use AI note-taking tools is important for promoting AI-assisted learning. Based on self-determination theory (SDT), this study examines the associations of processing fluency (PF) and learning agility (LA) with learners' BI to use AI note-taking tools, as well as the moderating role of cognitive load (CL), in online learning environments. A total of 380 questionnaires were collected, and 308 valid responses were retained after data screening. Structural equation modeling was used for analysis. Results showed that PF and LA were significantly and positively associated with perceived autonomy (PA), perceived competence (PC), and perceived relatedness (PR). PA, PC, and PR were significantly and positively associated with BI. However, PF and LA showed significant indirect associations with BI only through PC and PR, whereas the indirect associations through PA were not statistically significant. Furthermore, CL scores moderated several first-stage associations. The positive associations between LA and PA and between PF and PC were stronger at lower CL scores than at higher CL scores. Given the context-specific and positively scored CL measure, these findings indicate variations in the associations across CL score levels rather than differences between higher and lower overall cognitive load.

Keywords: AI note-taking; self-determination theory; processing fluency; cognitive load; behavioral intention

1. Introduction

In learning activities, note-taking is a common strategy that helps learners select and organize information and creates records for later review (Kiewra, 1989; Makany et al., 2009). Research has also examined the effects of structured note-taking systems in video-based learning (Fang et al., 2022). In synchronous and video-based learning, learners may need to process information as it is presented, with limited opportunities to revisit earlier content. These demands may increase the cognitive load (CL) involved in selecting, organizing, and integrating information during note-taking (Leppink et al., 2014; Klepsch et al., 2017). Today, AI applications have been explored in contexts such as automated training-material generation and collaborative qualitative analysis (Dietrich & Zwanzig, 2025; Gao et al., 2024). AI-assisted note-taking technologies, such as ChatGPT and Notion AI, have emerged accordingly, providing new possibilities for organizing and processing learning information. For example, MeetScript is a transcript-based system designed to support active participation in group video meetings (X. Y. Chen et al., 2023).

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Although AI-assisted note-taking offers new forms of information support, its implications for learning and engagement require further examination. On the one hand, some researchers have found that when AI-driven tools replace students' self-created original notes, learners' sense of ownership over their academic outcomes may be weakened (Chudaeva & Yuen, 2025). On the other hand, broader themes in AI ethics in education provide context for understanding the ethical considerations surrounding the use of AI tools (Yu & Yu, 2023). Previous studies have examined AI-assisted note-taking in relation to learners' cognitive engagement and learning processes (X. Y. Chen et al., 2025; Pi et al., 2026), but less is known about how information-processing experiences and adaptive learning characteristics relate to learners' behavioral intention (BI) to use these tools. Research on AI adoption has examined the associations of psychological factors, including trust and attitudes, with users' behavioral intentions (Peng et al., 2026; Xia et al., 2025). Given that learners' experiences with AI note-taking may be associated with processing fluency (PF) and may also be shaped by individual learner characteristics, such as learning agility (LA), the present study introduces PF and LA as key variables. PF reflects learners' subjective ease in understanding and processing AI note-taking content, whereas LA reflects learners' ability to adapt to new tools, new tasks, and new contexts (De Meuse et al., 2012). According to self-determination theory (SDT), perceived autonomy (PA), perceived competence (PC), and perceived relatedness (PR) are basic psychological needs associated with individuals' intrinsic motivation and intentions to use technology (Ryan & Deci, 2000). In technology-enhanced learning environments, the satisfaction of learners' basic psychological needs is closely related to their BI to use technology and their learning engagement. In online interactive teaching, SDT has been used to examine university students' deep learning (Q. Y. Zhou et al., 2024). The use of AI note-taking tools in online learning may introduce additional demands on learners' information-processing activities. Cognitive load theory (CLT) suggests that learners have limited cognitive resources, and CL may affect information processing and self-regulation. This study therefore examines whether the associations of PF and LA with PA, PC, and PR vary across scores on a context-specific CL measure.

To address this gap, this study integrates PF and LA into the SDT framework to examine their associations with PA, PC, PR, and BI toward AI note-taking tools. By examining both factors and the moderating role of CL, this study applies SDT to the context of AI-assisted note-taking and explores how these associations vary across CL scores.

2. Research Model and Research Hypotheses

2.1. Behavioral Intention to Use AI Note-Taking Tools in Online Learning and Self-Determination Theory

Research on online learning has examined note-taking across different media and methods, including mobile devices, mobile-phone photographs, digital pens, keyboards, and handwriting (Pyörälä et al., 2019; Mfaume et al., 2018; Shell et al., 2021; Morehead et al., 2019). Generative AI extends these approaches by automating note generation and information organization. However, AI note-taking tools have a dual impact on learning. On the one hand, AI-assisted note-taking may facilitate information organization, but its implications for learners' cognitive processing and engagement require further examination. On the other hand, overly complete and easily accessible AI notes may weaken learners' active processes of recording, selecting, and reflecting. Research in video-based STEM learning has compared learner-only, AI-only, and learner-AI collaborative note-taking and examined their relationships with cognitive load and learning outcomes (Pi et al., 2026). Other work has examined AI-assisted note-taking in relation to cognitive engagement and learning processes (X. Y. Chen et al., 2025). These findings suggest that learning with AI note-taking tools may depend not only on the clarity and structure of the information provided but

also on learners' ability to adapt to new tools and learning tasks. Understanding the factors associated with learners' BI is therefore important for explaining their willingness to adopt AI note-taking tools in online learning. Meta-analytic research has identified multiple factors associated with AI acceptance and adoption intentions in education (Ali et al., 2025). Research drawing on the expectation-confirmation model and the technology acceptance model (TAM) has also linked perceived ease of use and satisfaction to continuance intention toward AI-assisted search tools (Xia et al., 2026). The present study focuses on the associations between learners' psychological need satisfaction and BI toward AI note-taking tools.

SDT provides a framework for understanding learners' psychological need satisfaction and BI toward technology. It identifies autonomy, competence, and relatedness as three basic psychological needs relevant to motivation and well-being (Ryan & Deci, 2000). PA refers to learners' experience of volition and self-endorsed choice in learning activities, rather than merely their ability to control technological functions. PC concerns learners' sense of effectiveness and capability when engaging in learning tasks, which should be distinguished from perceived usefulness and general self-efficacy. PR, in its original theoretical sense, refers to feelings of social connection, belonging, and care in interpersonal relationships.

In AI-supported learning, users may perceive AI systems as responsive, supportive, or companion-like. These perceptions are not necessarily equivalent to interpersonal relatedness as conceptualized in SDT. This study therefore interprets PR as perceived relational support during interactions with AI note-taking assistants. This application builds on research using SDT to understand self-directed behavior in online learning (Chiang, 2025). Learners may evaluate AI note-taking tools more favorably when the tools support autonomous choices, learning tasks and responsive interactions. Such evaluations may be associated with stronger BI. Research on online learning linked support for autonomy, competence, and relatedness to positive psychological states and BI (Alsubaie et al., 2025). Other studies have examined autonomy and self-regulation in learning, as well as the application of SDT in STEM education (León et al., 2015; Moore et al., 2020). E-learning motivation has also been associated with technology acceptance and readiness (Rafiee & Abbasian-Naghneh, 2021). Together, these findings suggest that PA, PC, and PR may help explain BI toward AI note-taking tools.

2.2. Associations of Learning Agility with Perceived Autonomy, Perceived Competence, and Perceived Relatedness

Learning agility refers to individuals' ability to quickly adapt to new environments, learn from experience, and apply new knowledge (De Meuse et al., 2010, 2012; De Meuse & Harvey, 2022). In the context of AI note-taking, learners need to quickly understand, select, and integrate multiple sources of learning information, and adjust their use of AI note-taking according to learning tasks.

Learners with higher LA may be better able to adapt AI-generated notes to their needs, which may be associated with greater PA (De Meuse et al., 2010). LA has also been linked to adaptation, strategic adjustment, and PC in dynamic learning contexts. Research in educational technology and occupational behavior has reported a positive association between LA and creative self-efficacy (Gerçek & Özveren, 2025). Direct evidence linking LA to PR remains limited, although related studies offer indirect theoretical support. One study reported a positive association between LA and students' sustained learning engagement. It also suggested that learners with higher LA are better able to evaluate learning challenges and use existing knowledge to adapt to change (Jian, 2022). In AI-supported learning, learners may need to adapt to unfamiliar interaction patterns and interpret AI-generated feedback. Social presence has been discussed as a consideration in educational chatbot design (Huang & Hew, 2025), and perceived AI responsiveness and warmth have been

associated with trust and relational attachment (Lan et al., 2026). These findings suggest that learners with higher LA may be more likely to engage with AI note-taking assistants and perceive them as responsive and supportive learning companions. Accordingly, this study hypothesizes a positive association between LA and PR in the context of AI note-taking.

H1. *LA is positively associated with PA among learners using AI note-taking tools.*

H2. *LA is positively associated with PC among learners using AI note-taking tools.*

H3. *LA is positively associated with PR among learners using AI note-taking tools.*

2.3. Associations of Processing Fluency with Perceived Autonomy, Perceived Competence, and Perceived Relatedness

Processing fluency refers to the subjective ease of perceiving, understanding, or processing information about an object (Reber et al., 2004). When information is clearly presented and well organized, individuals may form more favorable cognitive evaluations and emotional responses. Previous research has identified PF as an important metacognitive experience. It reflects the subjective ease of information processing and is associated with individuals' judgments, preferences, trust, and behavioral decisions (Alter & Oppenheimer, 2009). In online learning contexts, learners need to complete multiple cognitive tasks, such as understanding course content and selecting information. As a generative artificial intelligence (GenAI) application in education, AI note-taking tools may support information processing through automatic transcription, key point extraction, and structured organization.

PA concerns volition and self-endorsed choice in learning activities. When AI-generated information is easy to process, learners may experience greater flexibility in organizing learning materials and making learning-related choices, which may be positively associated with their PA. PC concerns learners' sense of effectiveness in completing tasks. Previous research linking PF to self-efficacy and BI provides a basis for examining its association with PC (Kim & Jang, 2018).

Although self-efficacy and PC are conceptually distinct (Rodgers et al., 2014), stronger beliefs in one's ability to complete tasks may coincide with a greater sense of competence. Evidence linking PF to self-efficacy therefore offers indirect theoretical support for a positive association between PF and PC (Kim & Jang, 2018). In AI-assisted learning, learners who find AI-generated information easier to process may also report higher PC. PF may additionally be relevant to how learners perceive interactions with an AI assistant. Research in chatbot-based service and tourism contexts has examined how the match between chatbot persona and dialog style relates to PF, satisfaction, and use intention (Shams & Kim, 2026). Qualitative findings further suggest that natural and coherent chatbot responses can be perceived as signs of attentiveness and reliability (Wang et al., 2026). In addition, perceived responsiveness has been linked to feelings of social connection during human–AI interaction (Telari et al., 2026). These findings indirectly support the expectation that easier processing may coincide with more favorable perceptions of an assistant's responsiveness and support. This study therefore hypothesizes a positive association between PF and PR, operationalized here as perceived relational support in human–AI interaction.

H4. *PF is positively associated with PA among learners using AI note-taking tools.*

H5. *PF is positively associated with PC among learners using AI note-taking tools.*

H6. *PF is positively associated with PR among learners using AI note-taking tools.*

2.4. Associations of Perceived Autonomy, Perceived Competence, and Perceived Relatedness with Behavioral Intention

BI is a central outcome variable in technology acceptance research and typically refers to an individual's intention to adopt, continue using, or recommend an information technology (Davis, 1989). Here, BI concerns regular use of AI note-taking assistants, continued learning with their assistance, and future use for work or learning. Research on intelligent agents has linked perceived understanding of users' intentions and emotions to trust and BI (Peng et al., 2026). A study integrating TAM and SDT found that technology acceptance factors and psychological need satisfaction helped explain art and design students' use of GenAI image tools (Shen et al., 2025). An extended TAM has also been used to examine college students' intention to use AI coding assistants (Z. Pan et al., 2024). These findings suggest that learners' BI toward AI tools may be associated with both the functional characteristics of the tools and their psychological need satisfaction during use.

Specifically, PA emphasizes learners' experience of choice and behavioral control in the learning process. A study exploring the determinants of college students' adoption of GenAI tools in higher education found that PA was an important predictor of use intention (Tbaishat et al., 2026). In online learning, if learners can select learning content, adjust note structures, and arrange review schedules according to their own learning goals, they are more likely to regard AI note-taking as a tool that supports autonomous learning, which may be associated with stronger BI. PC emphasizes individuals' judgment of whether they can effectively complete tasks. Research on e-learning services has also reported a positive association between PC and use intention (Roca et al., 2006). Learners who perceive progress and achievement when using AI notes may likewise report stronger BI.

PR may also be relevant: perceived relatedness was positively associated with students' BI toward communicative AI in education (Cortez et al., 2024). In AI note-taking, learners who perceive an assistant as a supportive and dependable companion may report stronger intentions to continue using it. This proposed association concerns perceived relational support, rather than the functional match between a tool and a task. Accordingly, this study hypothesizes positive associations of PA, PC, and PR with BI.

H7. *PA is positively associated with BI among learners using AI note-taking tools.*

H8. *PC is positively associated with BI among learners using AI note-taking tools.*

H9. *PR is positively associated with BI among learners using AI note-taking tools.*

2.5. The Moderating Role of Cognitive Load

CLT and self-regulated learning theory emphasize that information processing, task monitoring, and goal regulation draw on limited cognitive resources. Cognitive load is relevant to resource allocation, self-regulation strategies, and metacognitive activity (Wirth et al., 2020). The relationships between learning strategies, monitoring, and outcomes may differ when tasks are complex or information-intensive (Gorbunova et al., 2024). LA may be associated with learners' perceived ability to adapt AI note-taking to their goals and, in turn, with PA, PC, and PR. However, the CL measure used here consists of positively scored, context-adapted items assessing information clarity, organization, redundancy, and comprehension support. The analyses therefore examine variation across CL scores without treating higher scores as evidence of higher overall cognitive load.

Research on cognitive load, learner resources, and self-regulation provides a theoretical basis for examining variation in these associations (Seufert et al., 2024). Given the present

operationalization, this study tests whether the associations of LA with PA, PC, and PR vary across CL scores. The following hypotheses are proposed:

H10. *The CL score moderates the relationship between LA and PA.*

H11. *The CL score moderates the relationship between LA and PC.*

H12. *The CL score moderates the relationship between LA and PR.*

PF reflects the ease with which learners process AI-generated information. Differences in the information-processing conditions captured by the CL measure may be associated with variations in the relationships between PF and psychological need satisfaction (Evans et al., 2024). Previous research has shown that cognitive load is associated with learners' judgments of their own abilities (Feldon et al., 2018; Zhang, 2024) and may also be associated with their perceptions of interactivity and supportiveness in online learning environments (Costley & Lange, 2018). Therefore, this study examines whether the associations of PF with PA, PC, and PR vary across CL score levels, rather than overall cognitive load levels. Based on this theoretical reasoning, the following hypotheses are proposed:

H13. *The CL score moderates the relationship between PF and PA.*

H14. *The CL score moderates the relationship between PF and PC.*

H15. *The CL score moderates the relationship between PF and PR.*

Figure 1 presents the research model and hypotheses.

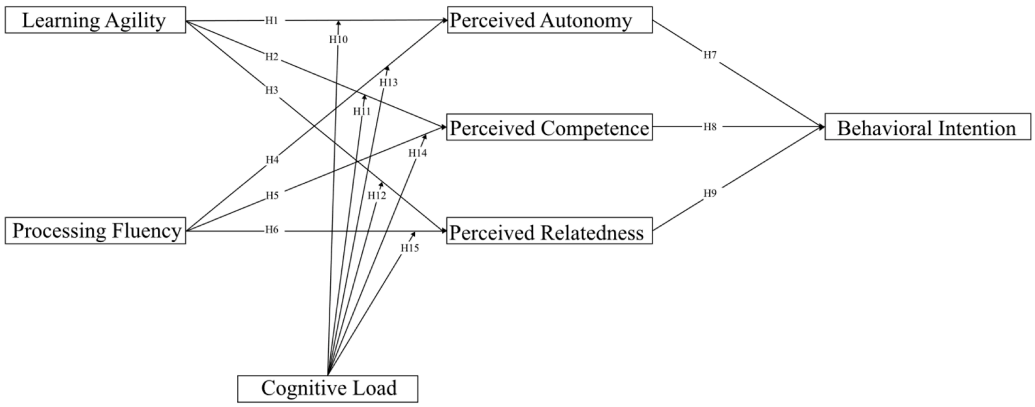


Figure 1. Research hypotheses.

3. Materials and Methods

3.1. Participants

The survey received 380 responses from undergraduate and postgraduate students and working professionals enrolled in adult self-study undergraduate education at Guangdong University of Technology. The working professionals were included because they were also engaged in online learning as part of their continuing education. Recruitment focused on individuals with experience using digital learning tools; eligibility required prior use of an AI note-taking assistant, as described in Section 3.3. Responses completed in less than 40 s or failing the attention check, which required selecting "2", were excluded. Of the 380 responses, 45 were excluded for completion times below 40 s and 27 due to failed attention checks, leaving 308 valid responses (81.05%). The final sample comprised 125 male

and 183 female participants. Their demographic characteristics are presented in Table 1. Demographic variables were used to describe the sample, and the attention-check item was used for screening; neither was included in the model analyses.

Table 1. Demographic characteristics ($N = 308$).

	Characteristic	*n*	Percentage (%)
Gender	Male	125	40.58
	Female	183	59.42
Age	18–25 years	275	89.29
	26–30 years	16	5.19
	31–40 years	6	1.95
	41 years or older	11	3.57
Educational level or participant status	Undergraduate	170	55.19
	Postgraduate	114	37.01
	Working professional	24	7.79

Note. Percentages may not total 100% due to rounding.

3.2. Research Tools

AI note-taking assistants extract and organize key information from text, audio, or video content and generate structured notes to support subsequent learning activities. As different AI note-taking tools may vary in their specific functions and interaction designs, this study focused on AI note-taking assistants as a general category of learning technology rather than on a single application. To provide a concrete illustration of the typical functions and usage of such tools, Tingnao AI was introduced as a representative example. Participants were not required to evaluate a specific application.

Tingnao AI (web-based version; https://itingnao.com/) provides several functions commonly found in AI note-taking tools, such as real-time speech transcription, automatic note generation, content structuring, and note export. A typical use process involves activating real-time recording during a learning activity, after which the system automatically transcribes the audio and generates structured notes with organized sections and key points. The generated notes can subsequently be reviewed online or exported for further learning activities. In the present study, Tingnao AI was used to illustrate the typical workflow and functions of AI-assisted note-taking rather than as the only application evaluated by participants.

The questionnaire was administered in Chinese, and the English item versions were prepared for reporting purposes without formal back-translation. The Chinese questionnaire was reviewed by the academic supervisor and pilot-tested with 76 participants before formal data collection. The pilot sample was collected separately and was not included in the final sample of 308 valid responses. The questionnaire consisted of three parts. The first part introduced AI note-taking assistants, describing their potential to organize information as well as possible omissions, misinterpretations, or mismatches with learning needs. The introduction was intended to familiarize participants with the research context. The complete original wording is provided in Supplementary Text S1. The second part collected demographic information, including gender, age, and educational level. The third part included measurement items for the seven variables in this study. First, the five LA items were contextually adapted from Bouland-van Dam et al. (2022), while De Meuse et al. (2012) and De Meuse and Harvey (2022) provided the theoretical basis. Second, the four CL items were contextually adapted with reference to CL research (Leppink et al., 2014; Klepsch et al., 2017), focusing on information clarity, organization, redundancy, and comprehension support. Specifically, the first three CL items address aspects of extraneous cognitive load (ECL)

related to information presentation, whereas CL4 was adapted to reflect comprehension support associated with germane processing (GCL-related). Intrinsic cognitive load (ICL) was not measured separately because this study focused on AI note-taking presentation features rather than directly manipulating the inherent complexity of the learning content. The CL score was calculated as the mean of the four positively worded items without reverse coding. Higher scores indicate more favorable responses to the aspects of CL assessed by these items, but do not directly indicate higher or lower overall CL. The theoretical basis and contextual adaptation of the items are presented in Supplementary Table S1. Third, the four items for PF were adapted for the AI note-taking context with reference to Graf et al. (2018) and Reber and Greifeneder (2017). Fourth, PA, PC, and PR were each measured using four context-specific items based on the three basic psychological needs in SDT (Ryan & Deci, 2000; Peters et al., 2018). Their application to digital technologies and conversational agents was informed by Yang and Aurisicchio (2021). PA4 was contextualized for the AI note-taking setting in line with the autonomy need in SDT. The PC items assess perceived capability and confidence, and the PR items focus on trust, support, and companionship in human–AI interaction. Finally, the three items for BI were adapted from Kreijns et al. (2014) and Venkatesh et al. (2003). An attention-check item was also included, namely, "Please select '2' for this item." All items and their reference sources are presented in Appendix A.

The questionnaire used a five-point Likert scale to assess respondents' perceptions of each item. This rating technique is suitable for survey research because its midpoint (3 = neutral) provides a clear distinction between positive and negative response options.

3.3. Data Collection

Data were collected through Wenjuanwang (web-based version; https://www.wenjuan.com/; accessed on 15 March 2026) from March to May 2026 using non-probability convenience sampling. An initial screening question, "Have you ever used an AI note-taking assistant?", stablished eligibility. Participants were recruited mainly through university-associated networks and WeChat, with additional questionnaire distribution through Xiaohongshu (https://www.xiaohongshu.com/) and Douban (https://www.douban.com/). A substantial proportion of participants were recruited through networks associated with Guangdong University of Technology.

Among the 308 valid respondents, 159 (51.62%) reported having used Tingnao AI (https://itingnao.com/), 129 (41.88%) DingTalk (https://www.dingtalk.com/), 116 (37.66%) NotebookLM (https://notebooklm.google.com/), 83 (26.95%) Youdao (https://note.youdao.com/), and 50 (16.23%) Tongyi (https://chat.qwen.ai/). Multiple responses were permitted so percentages do not sum to 100%. Eligibility required self-reported prior use of an AI note-taking assistant, with no minimum frequency or duration. Participation was voluntary, and informed consent was obtained before the survey. No identifying information was required, and participation had no bearing on academic evaluations or other benefits. Survey data were accessible only to authorized researchers. Consent forms and questionnaire responses were collected and stored separately to protect participants' confidentiality.

3.4. Data Analysis

Data were analyzed using IBM SPSS Statistics 27.0, AMOS 28.0, and PROCESS macro version 4.1 (Model 7). SmartPLS was used to obtain heterotrait–monotrait ratios (HTMT) and the supplementary cross-loading output. First, the measurement model was evaluated. Second, latent-variable structural equation modeling (SEM) in AMOS was used to estimate the hypothesized structural paths and indirect effects. Following previous research (L. Pan et al., 2024), and selected the chi-square/degrees of freedom ratio (χ^2/df), comparative fit index (CFI), Tucker–Lewis index (TLI), incremental fit index (IFI), and root mean

square error of approximation (RMSEA) as evaluation indicators. A χ^2/df value between 1.00 and 3.00 was considered acceptable. CFI, TLI, and IFI values above 0.90 were considered indicative of acceptable model fit. PROCESS macro version 4.1 (Model 7) analyses were conducted separately for LA and PF using mean composite scores. No covariates were included, and these analyses were conducted separately from the latent-variable SEM. Predictors were mean-centered before constructing the interaction terms. PROCESS is an established regression-based approach for examining moderation and conditional process effects (Hayes & Rockwood, 2017; Hayes et al., 2017). Bootstrap confidence intervals were estimated from 5000 resamples. Moderated mediation was assessed using the index of moderated mediation; a 95% bootstrap confidence interval excluding zero indicated statistical significance. The Benjamini–Hochberg false discovery rate (BH-FDR) correction was applied to the six first-stage interaction tests. Potential common method bias (CMB) was assessed using Harman's single-factor test (Fuller et al., 2016; H. Zhou & Long, 2004) and a confirmatory factor analysis (CFA) model incorporating a common method factor (CMF). The CMF model was compared with the hypothesized seven-factor model to assess whether it substantially improved fit. Procedural safeguards included voluntary participation and the absence of a requirement to provide identifying information.

4. Results

4.1. Measurement Model

Confirmatory factor analysis (CFA) was conducted to evaluate the construct validity of the measurement model. The results showed that the measurement model had a good fit (χ^2/df = 1.522, CFI = 0.962, TLI = 0.952, IFI = 0.962, RMSEA = 0.041). The Cronbach's alpha values of the seven latent variables ranged from 0.808 to 0.855, indicating acceptable internal reliability of the measurement instrument. Composite reliability (CR) was used to assess construct reliability, while average variance extracted (AVE) was used to assess convergent validity. All CR values were greater than 0.7, indicating good construct reliability within the fitted model. The AVE values all exceeded the threshold of 0.5, providing evidence of convergent validity of the measurement model (see Table 2). Discriminant validity was also examined using the Fornell–Larcker criterion (see Table 3). Four pairs of constructs did not meet this criterion: CL and PF ($r = 0.773$), PF and PR ($r = 0.743$), PC and BI ($r = 0.791$), and PR and BI ($r = 0.795$). Therefore, discriminant validity was not fully established. Discriminant validity was further assessed using the HTMT in SmartPLS (see Table 4). All HTMT values ranged from 0.441 to 0.791, below the 0.85 threshold, providing additional support for discriminant validity, although some overlap among constructs cannot be ruled out. To further assess discriminant validity, the original seven-factor CFA model ($\chi^2 = 500.363$, df = 329, CFI = 0.962, RMSEA = 0.041) was compared with a six-factor model combining PF and CL ($\chi^2 = 601.052$, df = 335, CFI = 0.940, RMSEA = 0.051). The superior fit of the seven-factor model provided additional support for distinguishing PF from CL. The 28 measurement items also showed evidence of multivariate nonnormality (multivariate kurtosis = 139.805, critical ratio = 29.930). The Bollen-Stine bootstrap test using 5000 samples was significant ($p = 0.016$), indicating that exact model fit was not supported, although approximate fit indices remained acceptable. Overall, these results provide evidence of acceptable reliability and convergent validity, while the comparison between the seven-factor and six-factor models provides additional support for distinguishing PF from CL.

Table 2. Reliability and convergent validity of the measurement model.

Construct	Item	Factor Loadings	Cronbach's α	AVE	CR
LA	LA1	0.733	0.852	0.540	0.854
	LA2	0.794			
	LA3	0.740			
	LA4	0.704			
	LA5	0.700			
CL	CL1	0.750	0.808	0.530	0.818
	CL2	0.784			
	CL3	0.622			
	CL4	0.746			
PF	PF1	0.752	0.828	0.547	0.827
	PF2	0.689			
	PF3	0.717			
	PF4	0.795			
PC	PC1	0.774	0.855	0.596	0.855
	PC2	0.774			
	PC3	0.749			
	PC4	0.790			
PA	PA1	0.712	0.811	0.531	0.818
	PA2	0.751			
	PA3	0.827			
	PA4	0.609			
PR	PR1	0.809	0.838	0.568	0.840
	PR2	0.712			
	PR3	0.811			
	PR4	0.674			
BI	BI1	0.780	0.838	0.635	0.839
	BI2	0.828			
	BI3	0.783			

Note. LA = learning agility; CL = cognitive load; PF = processing fluency; PC = perceived competence; PA = perceived autonomy; PR = perceived relatedness; BI = behavioral intention.

Table 3. Discriminant validity assessment using the Fornell–Larcker criterion.

	1. LA	2. CL	3. PF	4. PC	5. PA	6. PR	7. BI
1. LA	0.735						
2. CL	0.555	0.728					
3. PF	0.623	0.773	0.740				
4. PC	0.594	0.528	0.612	0.772			
5. PA	0.656	0.515	0.638	0.610	0.729		
6. PR	0.629	0.587	0.743	0.745	0.709	0.754	
7. BI	0.658	0.441	0.661	0.791	0.676	0.795	0.797

Common method bias (CMB) was assessed using Harman's single-factor test and a CFA model incorporating a common method factor. The first factor explained 40.697% of the total variance, below the commonly used 50% threshold. Adding a CMF resulted in only a marginal improvement in model fit, with CFI increasing from 0.962 to 0.963 and RMSEA remaining unchanged at 0.041. These results suggest that the inclusion of a CMF did not substantially improve model fit. These findings do not indicate a substantial improvement in model fit after accounting for CMF, although CMB cannot be completely ruled out.

Table 4. HTMT results for discriminant validity.

	1. CL	2. BI	3. PF	4. LA	5. PA	6. PC	7. PR
1. CL							
2. BI	0.441						
3. PF	0.791	0.660					
4. LA	0.565	0.652	0.624				
5. PA	0.540	0.681	0.658	0.663			
6. PC	0.539	0.787	0.608	0.593	0.635		
7. PR	0.595	0.783	0.734	0.616	0.724	0.740	

4.2. Structural Model and Hypothesis Testing

The SEM analysis was conducted using AMOS v28.0. The structural model demonstrated an acceptable fit to the data, with $\chi^2/df = 1.998$, CFI = 0.936, TLI = 0.928, IFI = 0.937, and RMSEA = 0.057. Multivariate nonnormality was observed (kurtosis = 122.136, c.r. = 30.338). Although the Bollen-Stine bootstrap test was significant ($p < 0.001$), the approximate fit indices remained acceptable. SEM was used to model and evaluate the hypothesized relationships included in the proposed research model. A bootstrap procedure with 5000 resamples and a 95% confidence levels was used. Table 5 presents the standardized path coefficients and related results of the proposed research model. The results showed that H1, H2, H3, H4, H5, H6, H8, and H9 were significant at the 0.001 level, while H7 was significant at the 0.05 level, as shown in Figure 2. The model explained 48.3%, 43.6%, 60.5%, and 68.2% of the variance in PA, PC, PR, and BI, respectively.

Table 5. Summary of hypothesis test results.

Hypothesis	Unstd.	S.E.	C.R.	*p*	Std.	Remark
H1 LA → PA	0.422	0.059	7.140	***	0.499	Supported
H2 LA→ PC	0.459	0.068	6.732	***	0.429	Supported
H3 LA→ PR	0.423	0.063	6.761	***	0.394	Supported
H4 PF → PA	0.400	0.058	6.925	***	0.483	Supported
H5 PF → PC	0.526	0.070	7.464	***	0.502	Supported
H6 PF → PR	0.704	0.074	9.503	***	0.671	Supported
H7 PA → BI	0.196	0.076	2.583	*	0.171	Supported
H8 PC → BI	0.402	0.064	6.291	***	0.445	Supported
H9 PR → BI	0.345	0.065	5.282	***	0.382	Supported

Note. * $p < 0.05$, *** $p < 0.001$.

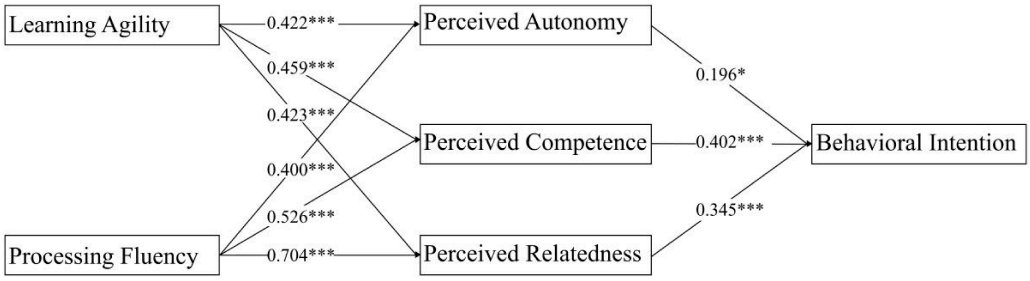


Figure 2. Structural model, * $p < 0.05$, *** $p < 0.001$.

An alternative model including direct paths from LA and PF to BI did not significantly improve model fit ($\Delta\chi^2(2) = 2.120$, $p = 0.346$). Neither direct path was significant, while the association between PA and BI became nonsignificant ($p = 0.100$).

4.3. Mediation Effects Analysis

The AMOS bootstrap analysis showed statistically significant indirect associations of PF and LA with BI through PC and PR. The 95% bias-corrected bootstrap confidence intervals for these four indirect effects did not include zero (Table 6). In contrast, the indirect effects through PA were not statistically significant, as their confidence intervals included zero. Specifically, the indirect effect of PF on BI through PA was 0.078 (95% CI [−0.022, 0.218], $p = 0.134$), while the indirect effect of LA on BI through PA was 0.083 (95% CI [−0.024, 0.226], $p = 0.128$). Overall, the indirect associations through PC and PR were statistically significant, whereas those through PA were not statistically significant.

Table 6. Bootstrapping estimates of unstandardized indirect effects on BI.

Indirect Path	Estimate	95% CI Lower	95% CI Upper	*p*
Ind1: PF → PR → BI	0.243	0.114	0.433	<0.001
Ind2: PF → PC → BI	0.211	0.106	0.385	<0.001
Ind3: PF → PA → BI	0.078	−0.022	0.218	0.134
Ind4: LA → PR → BI	0.146	0.055	0.304	<0.001
Ind5: LA → PC → BI	0.185	0.091	0.339	<0.001
Ind6: LA → PA → BI	0.083	−0.024	0.226	0.128

Note. Indirect effects were estimated using user-defined estimands in AMOS based on unstandardized coefficients. Bias-corrected 95% bootstrap confidence intervals were obtained from 5000 bootstrap resamples (N = 308).

4.4. Moderation and Moderated Mediation Analyses

Separate PROCESS Model 7 analyses were conducted to test the moderating effects of CL on the six first-stage paths from LA and PF to PA, PC, and PR. As shown in Table 7, some interaction terms were statistically significant. The results showed a statistically significant interaction between LA and CL in relation to PA (b = −0.163, t = −3.56, 95% CI [−0.253, −0.073]), supporting H10. However, the interaction effects of LA and CL on PC (b = −0.111, t = −1.90, 95% CI [−0.227, 0.003]) and PR (b = −0.046, t = −0.82, 95% CI [−0.156, 0.064]) were not significant. Therefore, H11 and H12 were not supported. In contrast, the interaction between PF and CL significantly predicted PA (b = −0.114, t = −2.13, 95% CI [−0.220, −0.009]), PC (b = −0.202, t = −3.03, 95% CI [−0.334, −0.071]), and PR (b = −0.136, t = −2.24, 95% CI [−0.255, −0.016]), which were nominally significant before BH-FDR (Benjamini & Hochberg, 1995) correction. After BH-FDR correction, the LA × CL interaction for PA and the PF × CL interaction for PC remained statistically significant. The interactions of PF and CL predicting PA and PR showed marginal significance (adjusted $p = 0.05002$ for both), slightly exceeding the conventional 0.05 threshold.

Simple-slope analyses were conducted at CL scores one standard deviation below and above the mean (Figure 3). As shown in Table 8, the positive associations of LA with PA and PF with PA, PC, and PR were stronger at lower CL scores than at higher CL scores. For example, the association between PF and PC was stronger at a lower CL score (b = 0.524, t = 6.77, $p < 0.001$) than at a higher CL score (b = 0.251, t = 2.83, $p = 0.005$). Given the context-specific and positively scored CL measure, these findings should be interpreted as variations in the associations across CL scores rather than direct evidence of differences in overall cognitive load.

Table 7. Moderating effects of cognitive load scores on the relationships between predictors and psychological needs.

Model	Mediator	Predictor	b	t	95% CI	FDR-Adjusted *p*	R^2	F
1	PA	LA	0.383	7.52	[0.282, 0.483]	_	0.368	59.12
		CL	0.183	3.69	[0.085, 0.280]	_		
		LA × CL	−0.163	−3.56 ***	[−0.253, −0.073]	0.002		
2	PC	LA	0.418	6.42	[0.290, 0.547]	_	0.322	48.02
		CL	0.297	4.66	[0.171, 0.422]	_		
		LA × CL	−0.111	−1.90	[−0.227, 0.003]	0.0700		
3	PR	LA	0.414	6.63	[0.291, 0.537]	_	0.349	54.21
		CL	0.354	5.81	[0.234, 0.473]	_		
		LA × CL	−0.046	−0.82	[−0.156, 0.064]	0.4120		
4	PA	PF	0.376	6.67	[0.265, 0.487]	_	0.313	46.17
		CL	0.119	1.99	[0.001, 0.237]	_		
		PF × CL	−0.114	−2.13 *	[−0.220, −0.009]	0.05002		
5	PC	PF	0.387	5.53	[0.249, 0.525]	_	0.307	44.92
		CL	0.202	2.71	[0.055, 0.348]	_		
		PF × CL	−0.202	−3.03 **	[−0.334, −0.071]	0.0078		
6	PR	PF	0.525	8.26	[0.400, 0.650]	_	0.401	67.73
		CL	0.160	2.36	[0.027, 0.293]	_		
		PF × CL	−0.136	−2.24 *	[−0.255, −0.016]	0.05002		

Note. Asterisks indicate nominal (unadjusted) significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). BH-FDR-adjusted *p* values are reported separately. Dashes (_) indicate that the corresponding effects were not included in the BH-FDR adjustment.

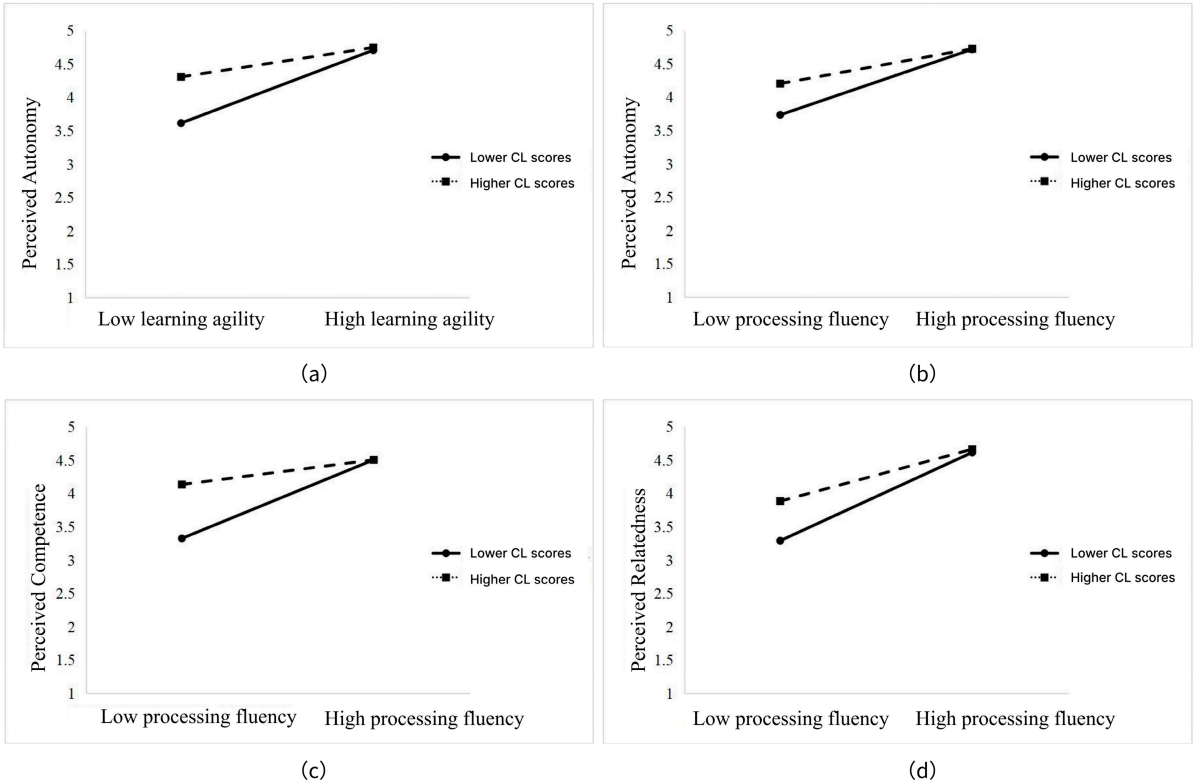


Figure 3. Simple-slope plots of the moderating effects of CL scores: (**a**) LA × CL on PA; (**b**) PF × CL on PA; (**c**) PF × CL on PC; and (**d**) PF × CL on PR. LA = learning agility; PF = processing fluency; CL = cognitive load; PA = perceived autonomy; PC = perceived competence; PR = perceived relatedness.

Table 8. Conditional associations at lower and higher CL scores.

Path	CL Score Level	Effect	SE	t	*p*	95% CI
LA →PA	Low	0.493	0.053	9.28	<0.001	[0.388, 0.598]
LA →PA	High	0.273	0.065	4.18	<0.001	[0.145, 0.401]
PF →PA	Low	0.454	0.062	7.28	<0.001	[0.331, 0.577]
PF →PA	High	0.299	0.071	4.19	<0.001	[0.159, 0.439]
PF →PC	Low	0.524	0.077	6.77	<0.001	[0.372, 0.676]
PF →PC	High	0.251	0.089	2.83	0.005	[0.076, 0.425]
PF →PR	Low	0.617	0.070	8.78	<0.001	[0.479, 0.756]
PF →PR	High	0.434	0.081	5.39	<0.001	[0.275, 0.592]

As shown in Table 9, the index of moderated mediation for the LA→PA→BI pathway was significant (index = −0.0691, BootSE = 0.0256, 95% Boot CI [−0.1167, −0.0130]), indicating that the indirect effect of LA on BI through PA varied significantly across CL scores. Similarly, the moderated mediation effect for the PF→PC→BI pathway was significant (index = −0.0974, BootSE = 0.0363, 95% Boot CI [−0.1621, −0.0178]). In contrast, the indices for the LA→PC→BI, LA→PR→BI, PF→PA→BI, and PF→PR→BI pathways were not significant because their bootstrap confidence intervals included zero. Thus, significant moderated mediation was observed in two of the six indirect pathways.

Table 9. Indices of moderated mediation.

Indirect Path	Index	BootSE	BootLLCI	BootULCI	Result
LA → PA → BI	−0.0691	0.0256	−0.1167	−0.0130	Significant
LA → PC → BI	−0.0537	0.0335	−0.1249	0.0137	Not significant
LA → PR → BI	−0.0220	0.0315	−0.0779	0.0507	Not significant
PF → PA → BI	−0.0489	0.0544	−0.1609	0.0447	Not significant
PF → PC → BI	−0.0974	0.0363	−0.1621	−0.0178	Significant
PF → PR →BI	−0.0654	0.0303	−0.1158	0.0038	Not significant

Note. BootSE = bootstrap standard error; BootLLCI and BootULCI represent the lower and upper limits of the 95% bootstrap confidence interval, respectively. Effects are significant when the 95% confidence interval does not include zero. Conditional indirect effects were estimated at CL scores one standard deviation below and above the mean (mean-centered values: −0.6743 and 0.6743).

The conditional indirect association between LA and BI through PA decreased from 0.2088 (95% CI [0.1154, 0.3170]) at low CL scores to 0.1156 (95% CI [0.0473, 0.2162]) at high CL scores. Similarly, the indirect association through PC for PF decreased from 0.2519 (95% CI [0.1494, 0.3575]) to 0.1205 (95% CI [0.0350, 0.2246]). Because higher CL scores reflect more favorable perceptions of information presentation and comprehension support, these results indicate that both conditional indirect effects were stronger at lower CL scores than at higher CL scores.

5. Discussion

5.1. Research Findings

Based on self-determination theory, this study examined the associations of LA and PF with learners' BI to use AI note-taking tools, focusing on the hypothesized indirect associations through psychological needs. AMOS-based SEM was used to examine the hypothesized direct and indirect paths, while PROCESS Model 7 was used to test the moderating and moderated mediation effects of CL. PF showed significant indirect associations with BI through PC and PR, whereas the indirect effect through PA was not statistically significant. In AI-assisted learning, learners who find AI-generated information easier to process may perceive greater flexibility in organizing learning materials and report higher

PA and PC, consistent with research linking information clarity and processing ease to individuals' subjective evaluations of tasks and materials (Reber & Greifeneder, 2017). Furthermore, higher PF may be associated with more favorable perceptions of AI note-taking assistants as responsive and supportive, corresponding to stronger PR during human–AI interaction. Although previous research has identified PA as an important predictor of students' intention to adopt generative AI tools (Tbaishat et al., 2026), the present findings did not support a significant indirect association between PF and BI through PA. This suggests that a positive association between PF and PA does not necessarily correspond to a statistically significant indirect association with BI.

LA showed statistically significant indirect effects on BI through PC and PR, whereas the indirect effect through PA was not statistically significant. Unlike PF, which mainly reflects the experience brought about by the presentation of tool-generated information, LA reflects learners' perceived ability to adapt to new tools and tasks. Higher LA was associated with higher PA, PC, and PR when learners used AI note-taking tools. This may suggest that learners with higher LA perceive greater flexibility in adapting AI note-taking tools to their learning needs. This finding is generally consistent with previous research, which suggests that LA is closely related to students' sustained learning engagement (Jian, 2022). The significant indirect associations through PC and PR further suggest that perceived competence and relational support may be particularly relevant to the relationship between LA and BI. However, these associations do not establish improvements in actual tool-use effectiveness or learning performance.

The results showed that CL moderated the association between LA and PA and the associations of PF with PC. Specifically, these associations were stronger at lower CL scores than at higher CL scores. For example, the association between PF and PC was stronger at a lower CL score ($b = 0.524$) than at a higher CL score ($b = 0.251$). The PF × CL interactions for PA and PR showed marginal significance after BH-FDR correction and should therefore be interpreted cautiously. Previous research has linked cognitive load with cognitive resource allocation and self-management during learning (de Bruin et al., 2020), while other studies have examined the relationships between learning adaptability, motivation, self-management, and self-regulation (She et al., 2023). These studies provide relevant theoretical context for interpreting the observed associations, although they do not directly establish the mechanisms underlying the present findings. Research discussing the relationship between CL and motivation may also offer a broader perspective (Evans et al., 2024). However, given the context-specific and positively scored CL measure, the observed interactions should be interpreted cautiously. The results indicate variations in the associations across CL scores but do not establish that these associations were stronger under higher overall CL. Individual differences in learning strategies may also contribute to the observed patterns, which warrants further investigation. In contrast, the moderating effects of CL scores on the relationships between LA and PC and between LA and PR were not statistically significant. These findings suggest that the moderating associations involving CL scores were not uniform across the three psychological needs. Beyond these first-stage moderation effects, the moderated mediation analysis showed that CL scores significantly conditioned the indirect association of LA with BI through PA and the indirect association of PF with BI through PC. Both conditional indirect effects were stronger at lower CL scores than at higher CL scores. No significant moderated mediation effects were observed for the other four indirect pathways, indicating that these conditional associations were pathway-specific rather than uniform across psychological needs. Notably, although the unconditional indirect effect of LA on BI through PA was not statistically significant in the AMOS mediation analysis, the significant index of moderated mediation in the PROCESS analysis indicated that this indirect association varied across CL scores. These findings

highlight the distinction between unconditional mediation and moderated mediation. The discriminant validity results also warrant attention. Four construct pairs did not fully meet the Fornell–Larcker criterion, suggesting potential empirical overlap among some constructs. In the AI note-taking context, CL and PF may be related because both concern learners' experiences of processing AI-generated information. Similarly, PC and BI, as well as PR and BI, may be closely associated because perceived competence and relational support are relevant to learners' intentions to continue using AI tools. Discriminant validity should be evaluated by considering theoretical distinctions and empirical evidence together rather than relying solely on a single cutoff (Rönkkö & Cho, 2022; Shaffer et al., 2016). Although the seven-factor CFA model fit better than the six-factor model combining PF and CL, this comparison provides additional evidence only for distinguishing PF from CL and does not resolve the concerns regarding the other construct pairs.

5.2. Theoretical and Practical Implications

This study makes two theoretical contributions. First, it integrates PF and LA into the SDT framework to examine their associations with PA, PC, PR, and BI in the context of AI note-taking. Second, the findings indicate that the association between PF and PC varies across CL scores. Given the context-specific measurement of CL, this interaction should be interpreted cautiously, and further research is needed to validate the measure and examine possible explanations. This process-oriented perspective extends previous research by examining these factors together in the context of AI-assisted note-taking, rather than treating technology acceptance and perceived support in isolation (Çobanogullari & Özbek, 2025; Liu & Ma, 2024).

From a practical perspective, these findings suggest several potential considerations for AI note-taking tool design and educational use. In online learning environments, AI applications may be designed to support learners' autonomy, competence, and relatedness through technology-mediated learning experiences. Developers may consider intuitive interfaces and tutorials to support users' PA and PC, although their effectiveness requires further evaluation. Educators may also consider providing guidance on AI tool use, subject to further empirical evaluation.

5.3. Limitations

Although this study provides valuable insights, several limitations should be acknowledged. First, the use of non-probability convenience sampling may have introduced selection bias. A substantial proportion of participants were recruited through university-associated networks, and most respondents were aged 18–25. Although the sample included working professionals engaged in adult undergraduate online learning, it may not adequately represent the broader population of online learners. Participants' institutional affiliations and geographic locations were not directly collected, which further limits the assessment of sample representativeness. Future research should recruit participants from more diverse institutions, regions, age groups, and educational backgrounds to further assess the generalizability of the findings. Participants' frequency and duration of AI note-taking tool use were not assessed, which may limit the interpretation of the findings. Future studies should consider differences in prior usage experience. Although the introduction mentioned both benefits and limitations of AI note-taking assistants, its positive framing may have influenced responses. Future research should use neutral descriptions to reduce potential response bias. Second, although Tingnao AI was used as an illustrative example, participants had experience with different AI note-taking tools. Differences in tool functions and interaction designs may have affected their responses. Future studies should evaluate specific applications or compare different tool categories to examine the robustness of the

findings. In addition, although an alternative model incorporating direct paths from LA and PF to BI was examined, these paths were not statistically significant. Future longitudinal studies could further investigate the direct and indirect associations among these constructs.

A further limitation concerns the context-specific measurement of LA, PA, PC, and PR. The LA items may capture perceived adaptability in AI-assisted learning rather than LA as a stable individual characteristic. The PA, PC, and PR items may also not fully capture their original theoretical meanings in SDT. In particular, PA4 may reflect perceived control over the assistant's functions more directly than PA, and this limitation should be considered when interpreting the findings. Future research could further examine their content validity across different AI-supported learning contexts. The four CL items were contextually adapted from cognitive load research but do not separately measure ICL, ECL, and GCL. Higher scores reflect more favorable perceptions of information presentation and comprehension, rather than higher overall CL. Although BH-FDR correction was applied, the risk of chance findings remains, and interaction effects near the significance threshold warrant cautious interpretation and further validation. Finally, the cross-sectional, single-source design limits causal interpretation and may be susceptible to CMB. Unmeasured factors, such as prior AI experience and technology attitudes, may also have contributed to the observed associations. Moreover, this study measured BI rather than actual tool usage or learning outcomes, which should be examined in future research.

6. Conclusions

Based on self-determination theory, this study examined how LA and PF were associated with learners' BI toward AI note-taking tools. The findings highlight PC and PR as important pathways linking LA and PF to BI, while the indirect effects through PA were not statistically supported. CL also moderated several relationships, suggesting that these associations varied across CL score levels. Given the cross-sectional design, the findings should be interpreted as statistical associations rather than causal relationships.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/bs16112142/s1: Table S1: Theoretical Basis and Contextual Adaptation of Cognitive Load Items; Table S2: Item-Level Descriptive Statistics of the Measurement Items (N = 308); Table S3: Cross-Loadings of Measurement Items (N = 308); Text S1: Questionnaire Introduction; Text S2: Additional References Supporting the Cognitive Load Measure (Koerber & Park, 2026, Krieglstein et al., 2023, Leppink et al., 2013).

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Institutional Review Board Statement: This study was approved by the Academic Ethics Committee of Guangdong University of Technology in March 2026. The ethics approval number is GDUTXS2026148. All participants provided written informed consent.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data available on request from the authors. The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Measurement Items and Their Sources.

Items	Source
A. Learning Agility (LA)	
1. With the assistance of an AI note-taking assistant, I am good at thinking about complex problems from different perspectives.	(Bouland-van Dam et al., 2022; De Meuse et al., 2012; De Meuse & Harvey, 2022)
2. I adjust my learning strategies based on feedback received during AI assistant note-taking activities.	
3. I am willing to try using the AI note-taking assistant to explore new learning strategies.	
4. With the assistance of the AI note-taking assistant, I can complete difficult learning tasks more effectively.	
5. I understand when to use the AI note-taking assistant to maximize learning effectiveness.	
B. Cognitive Load (CL)	
1. The AI note-taking assistant makes my learning content clearly structured and easy to understand.	See Supplementary Table S1 for item-level theoretical bases and adaptation details.
2. The AI note-taking assistant organizes the relationships among knowledge points clearly, making them easier to master step by step.	
3. The notes generated by the AI note-taking assistant are concise and do not contain redundant information that interferes with my learning.	
4. The functions of the AI note-taking assistant effectively enhance my understanding of core knowledge.	
C. Processing Fluency (PF)	
1. The knowledge structure provided by the AI note-taking assistant enables me to quickly locate the information I need.	(Graf et al., 2018; Reber & Greifeneder, 2017)
2. The summaries generated by the AI note-taking assistant make it easier for me to understand complex concepts.	
3. The note materials generated by the AI note-taking assistant are very clear and easy to read.	
4. The conceptual connections established by the AI note-taking assistant help me see the internal relationships among knowledge points.	

Table A1. *Cont.*

Items	Source
D. Perceived Competence (PC)	
1. I believe that I can skillfully use the AI note-taking assistant to support my learning.	(B. Chen et al., 2015; Peters et al., 2018)
2. I feel that I can complete learning tasks more efficiently.	
3. Using the AI note-taking assistant for collaborative learning often gives me a sense of achievement.	
4. I am very confident in using the AI note-taking assistant to support my learning tasks.	
E. Perceived Autonomy (PA)	
1. When learning, I have the freedom to choose which AI note-taking assistant to use to support my learning tasks.	(B. Chen et al., 2015; Peters et al., 2018)
2. I have the right to decide when to use the AI note-taking assistant to support my learning.	
3. I have the freedom to choose how to use the AI note-taking assistant in my learning.	
4. I can get the AI note-taking assistant to do what I want it to do.	
F. Perceived Relatedness (PR)	
1. I strongly trust this AI note-taking assistant and am willing to collaborate with it.	(Christoforakos et al., 2021; Peters et al., 2018; Yang & Aurisicchio, 2021)
2. I can feel that the design of this AI note-taking assistant sincerely aims to help me.	
3. This AI note-taking assistant makes me feel that it is a helpful partner.	
4. When learning with the AI note-taking assistant, I feel as though it accompanies me like a family member or a teacher.	
G. Behavioral Intention (BI)	
1. I plan to use the AI note-taking assistant as a regular learning tool.	(Kreijns et al., 2014; Venkatesh et al., 2003)
2. I am willing to continue learning with the help of the AI note-taking assistant.	
3. I also plan to use the AI note-taking assistant to support my future work or learning.	

Note. In the questionnaire items, "AI note-taking assistant" refers to the same category of technology as "AI note-taking tools" used in the main text. PA4 was contextualized for the AI note-taking setting based on the autonomy need in self-determination theory (SDT).

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