Student Responses to Cognitive Conflicts in GenAI-Assisted Learning: A Covariate-Dependent Markov Chain Analysis on Human-AI Interactions

Yiming Taclis Luo[1] | Ting Liu[1] | Patrick Pang[1] | Xiao Hu[2]

[1] Faculty of Applied Sciences, Macao Polytechnic University, Macao, Macao

[2] Faculty of Education, The University of Hong Kong, Hong Kong, Hong Kong

Correspondence: Patrick Pang (mail@patrickpang.net)

Abstract

Background:

As generative artificial intelligence (GenAI) reshapes the learning process, students will inevitably experience cognitive conflicts when their existing knowledge and beliefs clash with information provided by GenAI. Improper handling of cognitive conflicts may lead to a decline in students' learning efficiency and even hinder the development of critical thinking skills.

Objective:

This study aims to understand how students respond to cognitive conflicts during their interactions with GenAI, with a focus on comparing high-performing and low-performing student groups.

Methods:

To identify relationships between cognitive conflict intensity and students' responses, we used a covariate-dependent Markov chain (a sequential data modelling method) to analyse the 411 response states of students in a simulated academic writing task and observed transitions in student response states across different task performances.

Results:

The results revealed that the intensity of cognitive conflict had a significant impact on students' state transitions. Overall, as the level of conflict increased, students' state changes exhibited a phased pattern, shifting from fluctuation (transitioning to a variety of different states) to inertia or convergence (maintaining the original state or transitioning uniformly to a negative response state). Student response state transitions varied across different task performance levels.

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Conclusions:

This study provides a novel methodological perspective for modelling sequential response dynamics in Human-AI interaction. The findings offer new insights into the cognitive conflict dynamics in GenAI-assisted learning, providing implications for designing GenAI-assisted learning environments.

Lay Description

What is currently known about this topic?

- Cognitive conflict is a core driver of learning and knowledge reconstruction in constructivist theory.
- Students inevitably encounter cognitive conflicts when GenAI outputs contradict their existing knowledge or beliefs.
- Existing studies rely heavily on questionnaires and post hoc interviews, which cannot capture the dynamic nature of conflict response during human-AI interaction.

What does this paper add?

- Introduces a covariate-dependent Markov chain framework to model students' response state transitions as a function of cognitive conflict intensity.
- Operationalizes cognitive conflict intensity into three measurable levels based on knowledge discrepancy and conceptual complexity.
- Reveals a nonlinear regulatory pattern: as the intensity increases, students' response state gradually shifts to a stable state or a shift toward a negative response.
- Identifies strategic differences in students' responses to state transitions across different task performance levels.

Implications for practice and/or policy

- Educators may consider integrating explicit metacognitive skill-building into AI literacy curricula to help students regulate affective responses during high-intensity conflicts.
- Policy frameworks for GenAI integration in higher education could benefit from moving beyond questions of access and output accuracy to address the cognitive and affective demands that sustained human-AI interaction places on learners.

Keywords: cognitive conflict; GenAI-assisted learning; human-AI interactions; Markov chains; state transition

1. Introduction

According to constructivist theory, cognitive conflict refers to the contradictions that students find between their existing knowledge and new information, leading to challenges in decision-making processes (Li et al. 2021; Tan et al. 2025). In educational psychology, cognitive conflict is widely considered to be one of the core driving forces of students' cognitive development and deep thinking (Limón 2001). It is the key to motivating students to reflect, reconstruct knowledge, and achieve critical reflection and learning (Wang and Stein 2021; Zuo et al. 2024).

AI is reshaping people's perception of the students' learning process. In particular, generative artificial intelligence (GenAI) has been widely used in learning and teaching in higher education, becoming an important educational technology tool capable of adaptively responding to students' diverse inquiries (Luo, Liu, Pang, McKay, et al. 2026b; Niu et al. 2025). As a technology with both a vast knowledge base (Lu et al. 2024) and inherent logical limitations (Rodman and Topol 2025), GenAI offers convenience to learners, but the contradictions and uncertainty in its output inevitably create cognitive conflicts, complicating students' cognitive processes (Dehais et al. 2012).

The cognitive conflicts that students experience when studying in a GenAI learning environment are like a double-edged sword: On the one hand, moderate levels of stress and cognitive conflicts can effectively improve student performance and creativity (Pérez-Jorge et al. 2025), and the novel, unexpected ideas that GenAI brings to students can also benefit their thinking, decision-making, problem-solving, and creativity (Wood and Moss 2024). Essel et al. (2024) have found that the interaction with GenAI can effectively improve critical thinking by providing more personalized learning and interactive experiences, including reflective scepticism and critical openness (Essel et al. 2024). On the other hand, cognitive conflicts may also influence students' self-efficacy, beliefs, and GenAI usage behaviours (Zhu et al. 2025), and also bring about ethical risks (Yan et al. 2024). Left unaddressed, cognitive conflicts may escalate as the GenAI-assisted learning process continues, ultimately leading to negative outcomes and/or learning experiences such as confusion and frustration (Dai 2024).

Response states refer to the psychological and/or behavioural states exhibited by the student when encountering a cognitive conflict during interaction with GenAI (see Section 3 for more details). It is crucial to accurately identify and understand the response states related to cognitive conflicts in GenAI-assisted learning for timely pedagogical and strategic interventions. However, our understanding remains insufficient when it comes to the complexity of student-AI interactions. Existing research still exhibits several gaps. First, there is limited empirical evidence regarding cognitive conflicts encountered by learners using GenAI. Second, existing research into students' cognitive processes in GenAI-assisted learning relies heavily on questionnaires or post-interviews (Jaboob et al. 2024). These methods can only capture students' perceptions and recollections, which may be affected by memory bias. Furthermore, existing research lacks effective metrics to quantify cognitive conflicts

that occur during the learning process. This makes it difficult for researchers to systematically analyse how cognitive conflicts evolve over time, or to explore the impact of cognitive conflicts at varying intensity levels on learning.

To fill these gaps, we conducted a study on a GenAI-assisted academic writing task and collected 411 response states capturing the interaction process between students and GenAI. Each response state corresponds to AI output of different types. We treated each student-AI interaction as a potential cognitive conflict of varying intensity and then operationalized students' responses into three types: negative, neutral, and positive. In the meantime, the intensity of cognitive conflict is operationalized into three levels: low, medium, and high (readers are encouraged to refer to Section 3 for the details of our methodologies). For example, a rude interaction toward AI could be considered a negative response state following a high intensity level of cognitive conflict.

As previously seen, a response state (which includes types) is considered a representation of an episode of the interaction process, and a sequence of response states is used to model the interactive and cognitive processes of students over time. This study aims to explore the dynamic relationship between cognitive conflict intensity and the response states responding to cognitive conflicts in GenAI-assisted learning. To better guide this research, we propose the following research questions:

RQ1. In GenAI-assisted learning, do students with different task performances respond to cognitive conflicts differently? If so, what are the differences?

RQ2. In GenAI-assisted learning, do students respond to cognitive conflicts differently under different cognitive conflict intensities? If so, what are the differences?

To address these questions, we innovatively introduced cognitive conflict intensity as a covariate in the Markov chain model, transforming the otherwise ambiguous learning process into quantifiable probabilities of response states. A Markov chain is a mathematical model describing systems that move from one state to another. The core of a Markov chain is that all previous historical information has been condensed and reflected only through the current state, and the current state determines the next state (Häggström 2002). This approach offers three advantages over qualitative methods: it scales to large-scale sequential interaction logs; it enables quantitative observation of how a specific variable affects state transitions, supporting intervention analysis; and it produces explicit transition probabilities that capture how the likelihood of state changes shifts with conflict intensity.

In our context, how a student responds to AI's current output, that is, the current response state, depends only on their last interaction without the need for the entire interaction history. This assumption is also similar to the view emphasized by situated cognition theory that students' behaviour is not predetermined by plans, but is driven by contextualized and immediate actions in specific situations (Roth and Jornet 2013; Suchman 1987). It focuses on quantifying the immediate, direct impact of each conflict on the change of response state. This simplification allows us to effectively isolate the net effect of cognitive conflict intensity on response states.

By combining the theoretical framework of cognitive conflicts with dynamic quantitative models, this study provides a powerful new paradigm for understanding the complex cognitive processes in human-AI interaction. This approach can offer new insights into accurately identifying students' response states and provide empirical evidence for designing personalized and adaptive teaching interventions.

2. Cognitive Conflicts in the GenAI Era

The topic of cognitive conflicts is an important one in Piagetian constructivism and is considered essential to cognitive development (Lee and Yi 2013). Cognitive conflicts, as a fundamental component of the student learning process (Johnson and Johnson 2009), is described as a situation in which a series of mutually interfering processes occur simultaneously in the cognitive environment (Kang et al. 2004), and people notice the discrepancy between their own cognitive structure and the outside world (Lee et al. 2003). At this point, students should realize that they need to 'reframe', which in some way changes their existing ideas or concepts (Posner et al. 1982). Cognitive conflicts are intrinsically intertwined with both cognitive capacity and affective states. An individual's cognitive proficiency directly determines the differential availability of cognitive resources in conflict resolution, while affective characteristics (e.g., motivation, anxiety) dynamically modulate cognitive engagement. Previous research has predominantly focused on learners' epistemological beliefs (Hyytinen et al. 2014; Wu and Tsai 2011), emphasizing introspective judgements of self-held theories and concepts. However, scant attention has been paid to how interactive mechanisms within learning environments actively shape the emergence or mitigation of cognitive conflicts.

With the advent of GenAI technologies, educational ecosystems are undergoing a paradigm shift from static knowledge retrieval to dynamic interactive learning (Luo, Liu, et al. 2025; Luo, Liu, Pang, McKay, et al. 2026a). There is a need to fundamentally re-examine the cognitive conflict that arises in interactive learning scenarios supported by GenAI. The fundamental distinction between GenAI and traditional educational technologies is that GenAI is also regarded as an intelligent entity that appears to have general thinking ability (Schulz-Schaeffer 2025), which means it will interact with students in a more equal relationship in the form of peers or team partners. Therefore, the cognitive conflicts generated by the GenAI have both the characteristics of an internal team member and the external environment. As a result, the quality of learning is more easily affected by the intensity of cognitive conflicts, and may trigger emotional changes. The increase in cognitive intensity may reduce teamwork efficiency and task quality (Todorova et al. 2021). High levels of intensity in cognitive conflict can lead to fixed behaviours, decreased attention, and physiological stress, and are considered a precursor to the degradation of human-computer interaction (Dehais et al. 2012). GenAI's fluent output can trigger students' positive attitudes (Yang and Zhang 2024), while GenAI hallucinations can cause students' negative emotions such as anger and helplessness (Gabbiadini et al. 2025). This emotional fluctuation may further escalate the intensity of cognitive conflict, which will lead to risks and challenges in GenAI-assisted learning.

3 Methodology

3.1 Experimental Design

In a GenAI-assisted learning environment, it is vital to conduct appropriate experiments to observe students' behaviours and reactions when they encounter cognitive conflicts. To achieve this, the experimental setting needs to meet the criteria of *complexity* (Li et al. 2026) and *interdisciplinary* (Chen et al. 2024).

Complexity ensures tasks cannot be solved instantly by GenAI, forcing students to navigate ambiguity and problem-solving barriers with multiple steps and back-and-forth interactions. It also requires that the tasks set should be broken down or explored iteratively to capture the conflicts in students' overall cognitive process. *Interdisciplinary* fully utilizes the search advantages of GenAI, while creating real cognitive conflict and disharmony scenarios through the collision and integration of multiple fields.

This study designed an academic writing task in an experimental setting where participants were recruited to complete the task individually in a laboratory. Such designs are widely adopted in educational and learning sciences research, including recent work on GenAI-assisted learning (Tsai 2025; Wang, Wang, and Solhi 2025). Students were provided with a learning analytics dataset and asked to collaborate with GenAI to explore potential insights within the dataset. Additionally, students were asked to write a short academic essay using GenAI (see **Appendix A** for the specific materials and requirements). In the GenAI-assisted learning environment, whether the information is accurate, partially correct, or fabricated (GenAI may output incorrect or false information, known as GenAI hallucination), it may constitute a potential cognitive conflict if it contradicts the student's existing knowledge or beliefs, and students were free to suspect and question output from GenAI.

Figures 1 and **2** show the customized GenAI platform and the dataset used in this experiment. The platform was built using the ChatGPT-4o API and did not use any fine-tuning or pre-prompts. The purpose of using such a platform was mainly to capture students' interactions and potential cognitive conflicts, while providing a neutral and consistent starting point for all participants in this experiment.

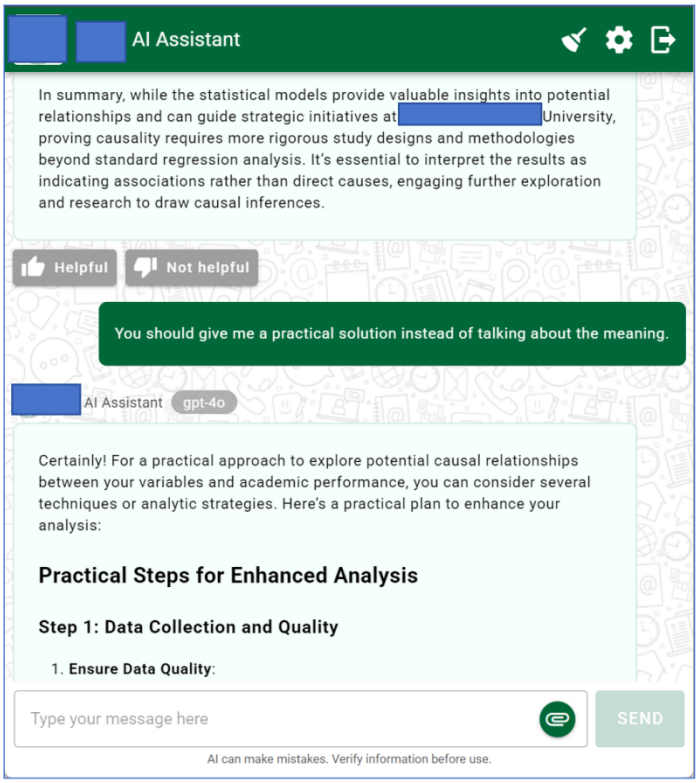


Figure 1. Screenshot of the experimental platform.

id	first_name	last_name	email	gender	part_time_jo	absence_c
1	Paul	Casey	paul. casey	male	FALSE	3
2	Danielle	Sandoval	danielle. s	female	FALSE	2
3	Tina	Andrews	tina. andre	female	FALSE	9
4	Tara	Clark	tara. clark	female	FALSE	5
5	Anthony	Campos	anthony. c	male	FALSE	5
6	Kelly	Wade	kelly. wade	female	FALSE	2
7	Anthony	Smith	anthony. s	male	FALSE	3
8	George	Short	george. sh	male	TRUE	2
9	Stanley	Gutierrez	stanley. g	male	FALSE	6
10	Audrey	Simpson	audrey. sir	female	FALSE	3
11	Gabrielle	White	gabrielle.	female	FALSE	2
12	Clinton	Randolph	clinton. r	male	FALSE	1
13	Patricia	Gomez	patricia. g	female	TRUE	7
14	Pamela	Jackson	pamela. jac	female	FALSE	10
15	Laura	Jackson	laura. jack	female	FALSE	3
16	Roger	Wiley	roger. wile	male	FALSE	6
17	Vicki	Thompson	vicki. thor	female	FALSE	3

Dataset Features:

ID: Unique identifier for each student.

First Name: The first name of the student.

Last Name: The last name of the student.

Email: The email address of the student.

Gender: The gender of the student (e.g., male, female).

Part-Time Job: Boolean indicating if the student has a part-time job.

Absence Days: Number of days the student was absent.

Figure 2. The dataset used in the student task with feature descriptions (all student names are pseudo-names).

The pre-experiment training phase included two parts: (1) a 45-min special lecture systematically explaining the operating specifications of the GenAI tool, and (2) a 20-min practical exercise to help the subjects master the basic functions of the platform. During the formal experiment, students obtained research tasks through a self-developed online platform and were allowed to freely use conventional auxiliary tools, including search engines, but the core interactions were limited to the designated GenAI interface. With the consent of the participants, we retained the chat records and screen recordings between the students and GenAI, which captured the text prompts and pictures sent by the students. After completing the experiment, students were required to submit a report on the given task. After the GenAI sessions, we conducted a semi-structured interview with each student. We showed participants screen recordings of their interactions with GenAI and their prompts. Students were asked to comment on cognitive conflicts and recall and articulate their cognitive activities and reasoning processes at the moment of interaction. Following the stimulated recall, the interview transitioned into a general discussion to solicit their perceptions of the entire GenAI-assisted learning process and their reactions and feelings toward all cognitive conflicts therein.

3.2 Determination of Types of Response States and Cognitive Conflict Intensity

Given the complexity of defining and quantifying cognitive conflicts (Smedslund 1961), the interaction prompts between students and GenAI and the responses of GenAI are considered as a set of potential cognitive conflicts. Sequences were aligned along the timeline based on multi-dimensional data sources such as screen recordings and interaction text records. Two doctoral students in educational technology also reviewed these time series data to ensure the consistency of the process.

Berlyne described cognitive conflict as ‘a condition in which mutually interfering processes occur simultaneously and in which selection of a motor response from a set of competing alternatives is therefore hampered’ (p. 968) (Berlyne 1970). Hewson (1988) and Stavy and Berkovitz (1980), within Piaget's theoretical framework, refined it as the conflict between students' existing concepts and experiences (Hewson 1988; Stavy and Berkovitz 1980). Based on this, this study operationalizes cognitive conflict as a state of psychological disharmony or contradiction that students experience when faced with inconsistencies between their existing knowledge, beliefs, or understanding and new information they encounter. Cognitive conflict intensity refers to the objective severity of a cognitive conflict, measured by the characteristics of the conflicting information itself. Vandenplas-Holper chose the sum of the number and degree of discrepancies and disagreements faced by students to measure the cognitive conflict intensity (Vandenplas-Holper 1996). Based on prior research on factors contributing to cognitive conflicts, cognitive conflict intensity is measured using two objective dimensions in this study: (1) the discrepancy between the output from AIs and the students' existing beliefs or experiences (Lee et al. 1999), and (2) the conceptual complexity of the output from AI (Vandenplas-Holper 1996).

Through analysis of students' retrospective interviews and the GenAI output, we coded

the two dimensions of cognitive conflict intensity into three levels: low, medium, and high, with numerical scores from 1 to 3, as shown in **Table 1**. We calculated the final cognitive conflict intensity by multiplying the scores of knowledge discrepancy and conceptual complexity, and then categorized the product into low (1–2 points), medium (3–4 points), and high (5–9 points) levels. Two doctoral students independently coded the results, achieving acceptable inter-rater reliability (Cohen's $\kappa = 0.71$). An author served as an independent arbitrator, resolving discrepancies found between the two primary coders and determining the final coding results. Examples of cognitive conflicts in different intensity levels are shown in Figure 3. Students' task performance was not categorized during coding. We only categorized the intensity of knowledge conflict (low, medium, high) and the type of response state, and therefore did not judge different student performance levels.

Table 1. **Scoring dimensions of cognitive conflict intensity.**

Dimension	1. Point (Low)	2. Points (Medium)	3. Points (High)
Knowledge discrepancy	The output differs only slightly from the student's existing beliefs or experiences, involving only minor differences in detail.	The output differs from the student's existing beliefs or experiences in some aspects, involving some logical or conceptual differences.	The output differs significantly from the student's existing beliefs or experiences, involving conflicts with core concepts or key conclusions.
Conceptual complexity	The conflict involves only one simple concept or only contains judgements.	The conflict involves two or three related concepts or requires simple reasoning.	The conflict involves four or more related concepts or requires complex reasoning or abstract thinking.

Student response refers to the specific behaviours or psychological activities exhibited by students after a cognitive conflict occurs. Student response state is a classification or summary of student responses. Measuring student responses involves multiple dimensions. Chan et al. applied an 11-point Likert scale to assess students' belief changes (Chan et al. 1997). Kang et al. divided students' responses to cognitive conflicts into multiple states, including rejection, reinterpretation, uncertainty, marginal belief change, belief weakening, and belief transformation (Kang et al. 2004). Given the complexity of defining student responses, we engaged four experts to determine the type of response state based on the specific context. These experts included: (1) a professor with a PhD in Psychology and 8 years of teaching experience; (2) a professor with a PhD in Computer Science and a senior engineer qualification in information engineering; (3) a research assistant specializing in computational media studies with 3 years of technical development experience; and (4) a doctoral student in Educational

Technology with 2 years of teaching experience. Before starting to code student responses, the experts had a discussion meeting to examine a random sample of the dataset and define the types of student response states. To start the discussion, we provided three abstract categories of response states, namely ‘negative’, ‘neutral’, and ‘positive’, without pre-set static definitions. To encourage the experts to express their understanding of student responses under cognitive conflict based on examples presented in the sample data. A total of 84 interaction segments from 5 students (20.43% of the dataset) were used as cases for discussion, including time-aligned chat logs between AI and student, student interview transcripts, and corresponding screen recordings. The discussion lasted approximately 3.5 h and involved a detailed examination of each segment, resolving ambiguities and agreeing on coding criteria. The remaining segments (79.57%) were independently coded by all experts. When discrepancies occurred among the experts, the final code for each segment was determined by majority rule. In case of ties, the first author served as an arbitrator to decide the final code for the segment.

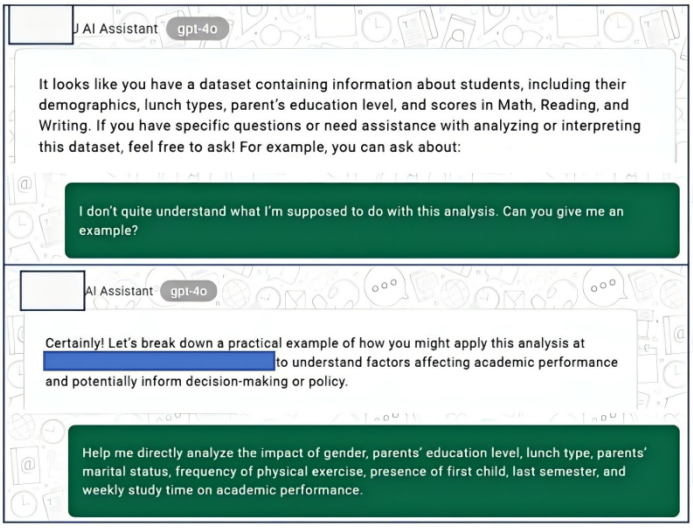
From an interpretive perspective, understandings of these response states are not fixed truths but rather social constructs built through dialogue and consensus (McKay et al. 2024). Although the experts' initial judgements came from diverse academic backgrounds, their views converged through discussion, resulting in a core, intuitive definition of the response state after experiencing cognitive conflicts. The definitions of response states and examples are presented in **Table 2**, where the categories, *negative*, *neutral*, and *positive* are referred to with numerical codes 1, 2, and 3. Fleiss's Kappa among all codes from the four experts was 0.795, indicating good overall consistency and confirming the reliability of the codes.

Table 2. Description of the types of response states.

Code	Description	Example
Negative	When faced with cognitive conflicts or discrepancies, students show negative responses, including pointing out errors, rejecting opinions, and criticizing answers.	'There's something wrong with your calculation'. 'Don't use machine learning algorithms on me. The purpose of my research is not to predict'.
Neutral	No clear observation of students' behavioural tendencies in response to cognitive conflicts. This includes uncertainty about the timing of cognitive conflict or the need for further confirmation, including re-editing the prompt text or regenerating or reinterpreting the GenAI.	'Continue with your previous formula'. 'Can you explain the solution you gave in another way?'
Positive	When faced with cognitive conflicts or discrepancies, students showed positive responses, including full acceptance of GenAI's opinions, praise or encouragement, changing some of their ideas, and continuing with instructions.	'Then use cluster analysis as you said'. 'Then please help me adjust the format of my document according to the suggestions you gave me before'.

Finally, we integrated the collected data, including prompts, screen recording information, and interview materials, and performed time alignment on all codes. To provide a more intuitive and coherent understanding of how our encoding maps to students' behaviours, **Figure 3** shows a fragment of a combined interactive process and a stimulated recall interview. Initial interactions are smooth and efficient (as shown in Sub-Figure (a) in **Figure 4**); however, as the process progressed, the student's requests for analysis were met with a deluge of useless and incomprehensible information, and he/she expressed frustration in retrospective interviews. Yet, he/she continued to demonstrate a tendency for proactive thinking. Following communication failures, the strong emotional expressions and prolonged focus on coding issues during the interviews indicated the intensity of cognitive conflict (Figure 3b), and he/she described the GenAI as 'pointless' and 'a waste of time', and tended to refuse the GenAI's assistance.

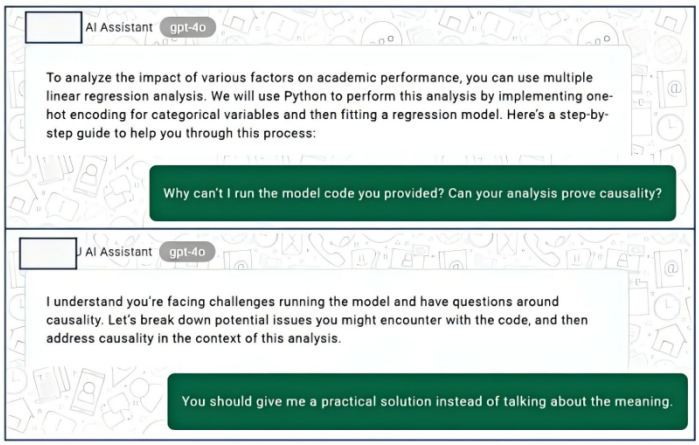
(a) *Transition: Positive (Intensity : Low) →Neutral (Intensity : Medium)*



"...This is my first time using this GenAI model. The model runs quite fast. I asked it questions about the task description and it responded to me quickly..."

"...I asked it to help me analyze it, but it threw a lot of content at me without explaining it. I couldn't understand it and didn't have the patience to finish it..."

(b) *Transition: Negative (Intensity : Medium) →Neutral (Intensity : High)*



"...I was a little annoyed because I didn't know how to run the code it gave me. I have no coding experience. Then I did ask about causality, because I remembered that I learned about this concept in statistics class, so I guess I need to test it here?..."

"...It keeps talking in circles and doesn't provide any real help. It's pointless and a waste of time. I don't agree with what it says, and I'm not satisfied with the explanations it provides...."

Figure 3. Example of student cognitive conflict process segments (quotes next to each sub-figure are the corresponding stimulating interview transcripts arranged in chronological order after time alignment).

3.3 Statistical Models

This study established a covariate-dependent Markov state model to describe the dynamic process of student-AI interactions (Luo et al. 2026), as shown in Formula (1). It states that the conditional probability of the next state S_{t+1} is only related to the current state S_t and the current covariates INT_t (intensity of the cognitive conflict in time t), and the constraint ensures that the sum of the probabilities of all possible target states S_{t+1} is 1 for any given S_t and any INT_t.

$$P(S_{t+1} \mid S_t,\mathrm{INT}_t,S_{t-1},\mathrm{INT}_{t-1},\dots)=P(S_{t+1} \mid S_t,\mathrm{INT}_t) \quad (1)$$

where $\sum_{k\in\{\mathrm{Neg,Neu,Pos}\}} P(S_{t+1}=k \mid S_t=i,\mathrm{INT}_t)=1$ for all $i\in\{\mathrm{Neg,Neu,Pos}\}$.

After defining the states, multinomial logistic regression (MLR) with the *softmax* function is applied to calculate the exact probability of the students' next state by taking their current state and conflict intensity while satisfying the constraint. In MLR, a state category needs to be selected as the baseline category, relative to which the coefficients of other categories are estimated. Generally, the category with the largest and most representative data volume is selected as the baseline category, so we chose the negative in this study.

Formula (2) shows the probability of the system transferring to state k given the current S_t and INT. The coefficients in the model determine which factors have the greatest impact on the student's next state. β_{0k} represents the intercept term of k. It means the default probability of a student transitioning to state k, assuming no other factors are at play. β_{1k} represents the influence coefficient of INT on the transition to k. It tells us how the intensity of a cognitive conflict changes the default probability. For example, a large positive coefficient for the transition to a 'negative' state would mean that as a conflict gets more intense, students are more likely to exhibit negative reactions, such as frustration and refusal to communicate.

$$P(S_{t+1}=k \mid S_t, \mathrm{INT}) = \frac{e^{\beta_{0k}^{(t)} + \beta_{1k}^{(t)} \cdot \mathrm{INT}}}{\sum_j e^{\beta_{0j}^{(t)} + \beta_{1j}^{(t)} \cdot \mathrm{INT}}} \quad (2)$$

3.4 Educational Interpretation of the Model

A state transition is considered to be the student's response to a cognitive conflict, referring to a change in attitude and/or cognitive stance in the learning process. In this study, we use a Covariate-dependent Markov chain model to calculate the probabilities of transitions among different states. It is based on this quantification that the results of our model can provide a concrete way to explain educational phenomena.

For instance, when a group of students' transition probability reveals a high likelihood of remaining in negative states or cycling repetitively between negative and neutral states, with a very low probability of moving to a positive one, this may typically suggest a student's tendency to quickly settle on an answer or belief without seeking more information or critically considering other perspectives.

Another common behaviour pattern among students in GenAI-assisted environments is behavioural volatility, which is the rapid change in a student's responses during interaction. Research has found that students may lack independent judgement and overly quickly accept and trust GenAI's output and perspectives, frequently shifting their own opinions (Wang, Li, et al. 2025). Volatility can be quantified by measuring the dispersion of transition probabilities. In other words, if a group of students has similar probabilities of transitioning among positive, neutral, and negative states, this reflects high volatility and low state stability. In a Covariate-dependent Markov chain model, low state stability can be reflected by two indicators in the transition matrix:

first, the diagonal elements in the transition matrix have low probabilities (e.g., low probability of positive to positive), indicating that students' response states are unstable and difficult to maintain in any particular emotion; second, the off-diagonal elements in the transition matrix have high probabilities (e.g., high probability of positive to neutral), meaning that students' response states change frequently and unstable.

The framework also offers two methodological advantages, scalability and precision: First, unlike qualitative approaches that require rich annotation for every observation, this framework can be applied to large-scale sequential interaction logs and allows researchers to introduce specific variables of interest as covariates. Second, the model produces explicit transition probabilities, enabling quantitative observation of their effects on state transitions and supporting intervention analysis by simulating how changes in a given variable would alter students' response state trajectories, which is a level of analytical granularity that thematic or qualitative approaches cannot provide.

The detection of this emotional volatility is crucial because, according to self-regulation theory, it may suggest that students lack stable metacognitive strategies and have difficulty effectively managing the cognitive demands of the task (Iran-Nejad 1990). Given that these cognitive phenomena are difficult to observe through conventional methods, our model provides insights into students' dynamic cognitive processes and can effectively detect how students with different performances cope with cognitive conflicts, laying an empirical foundation for providing intervention measures.

3.5 **Performance Grouping**

Two doctoral students specializing in educational technology and a computer science expert evaluated and scored the results according to Nguyen's standards for AI-supported writing (Nguyen et al. 2024). The rubrics for task assessment contain five criteria, each on a 4-point scale: Content, Analysis, Organization & Structure, Quality of Writing, and Word Limit & Referencing (see **Table A1**).

Evaluating student behaviour or output based on performance across different tasks is a common practice in learning analytics (Gu and Yan 2025). Based on this evaluation standard, we also conducted a between-group analysis to divide the post-task grouping participants into high- and low-performance groups to further compare the response states of students with different task performances when dealing with cognitive conflicts.

We used a hybrid K-means clustering algorithm (K = 2) on task scores (Luo, Pang, and Chang 2025). K-means is an unsupervised learning method that can autonomously discover hidden and unrecognized group-based structures from data. Compared with the basic statistical method that relies on the average or median value, this K-means algorithm is more suitable for processing the multidimensional data of task scores.

4 Results

4.1 Participants

The experiment recruited 21 first- to third-year undergraduates from two English-medium universities in China. A total of 411 (M = 19.57, SD = 4.48) response states were collected. 52.4% of students are male (N = 11), and the rest are female. 61.9% of students are from the Faculty of Science and Technology, and 28.6% are from the Faculty of Business Management. The remaining students are from the Faculty of Humanities and Social Sciences. Pre-surveys indicate that all participants possess a certain level of digital literacy and experience using GenAI.

As illustrated in **Figure 4**, after clustering with the K-means algorithm, the data were clustered into two groups with different task performance levels. Non-parametric tests showed that there was a statistically significant difference between these groups (U = 0.17, $p < 0.01$).

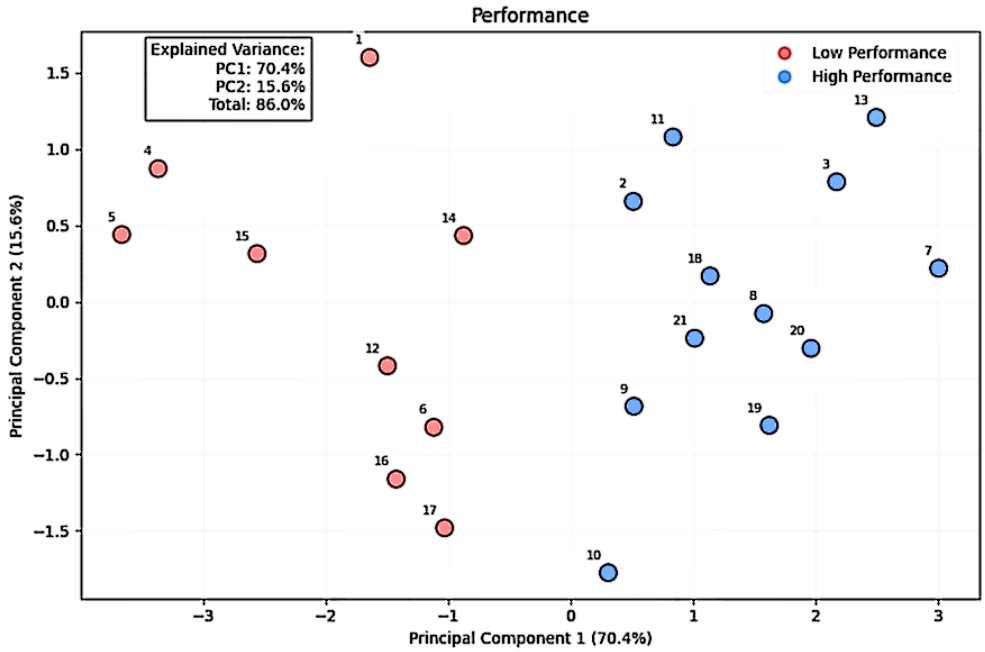


Figure 4. Student sample clusters after K-means clustering through principal component analysis.

4.2 RQ1: Cognitive Conflicts Among Students at Different Performance Levels

After clustering and distinguishing the different performance groups of students, we have renumbered the students in these groups. **Figure 5** shows a time-series line graph of the students' cognitive conflict response states during their interaction with GenAI. Each subgraph represents a student's state sequence during the learning phase. The line pattern illustrates the transitions in the student's state responses during interaction with the system. **Figure 6** shows the transition probabilities of different groups of students under this system. Each node represents one of the three response states expressed during the interaction. The arrows indicate the direction of the next state transition, and

the values represent the probability of the next state transition.

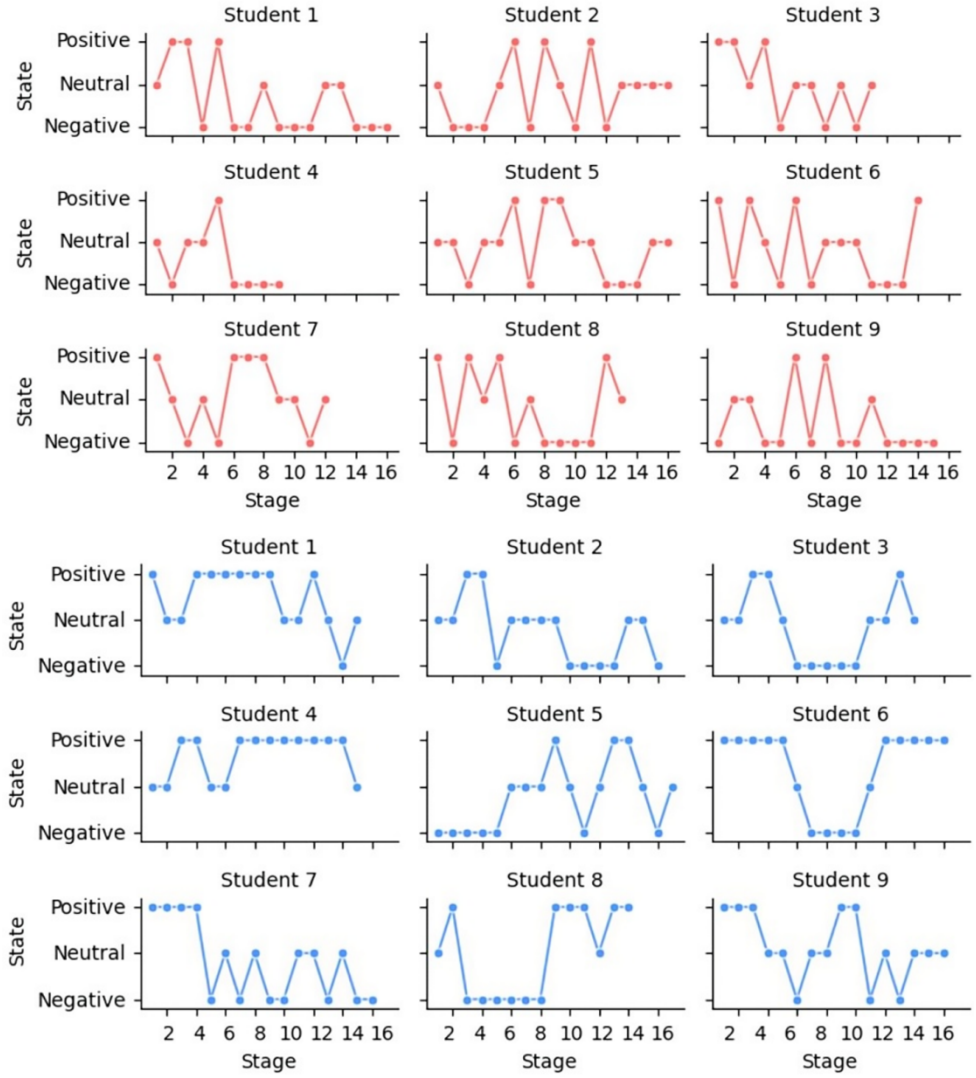


Figure 5. Time series of states of student samples clustered in different performance groups. Red and blue represent low task performance and high task performance student samples, respectively.

In the high-performing group, students' frequency of transition from positive to positive was extremely high, accounting for 67.1% of all positive transition categories, indicating that high-performing students have a stronger persistence in maintaining positive feedback, such as adjustment or reception, when cognitive conflicts occur. In the low-performing group, this situation only accounted for 18.5%, and more turned to neutral or negative states. In addition, in the high-performing group, students rarely jump directly from a *negative* state to a *positive* state, which indirectly reflects a relatively stable strategy for cognitive conflicts.

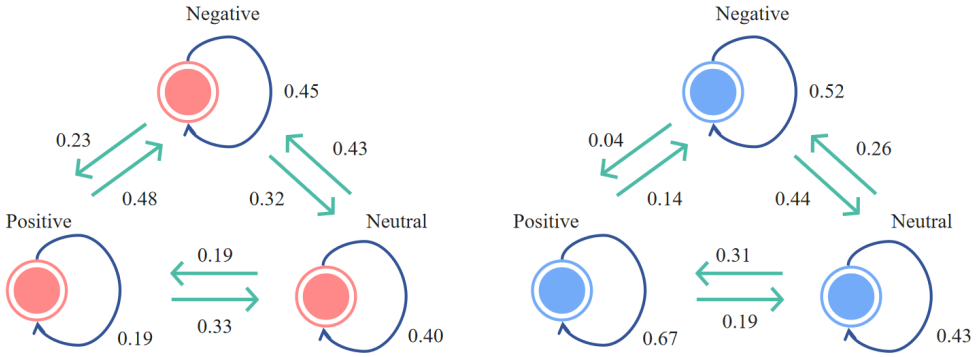


Figure 6. Transition probability plot of matrix elements for different groups of students with different performances, where red represents the low-performance group and blue represents the high-performance group.

4.3 RQ2: Responding to Cognitive Conflicts Under Different Cognitive Conflict Intensity

Figure 7 presents the probability diagram of the state transition of students with different performances under different cognitive conflict intensities. High-performing students demonstrate remarkable response inertia to cognitive conflict in low-intensity situations, meaning they maintain consistent reactions and approaches when encountering GenAI conflicts of minimal intensity. In contrast, low-performing students exhibit unstable response patterns. They display a greater initial willingness to provide positive feedback and endorse perspectives suggested by GenAI, though this affirming attitude proves unsustainable. When conflict intensity reaches moderate levels, high-performing students show a different response state. Low-performing students become significantly more prone to self-doubt (evidenced by a marked increase in transitions from *negative* to *neutral* states). Their responses increasingly default to neutral positions while largely abandoning previously affirmative or accepting stances. Interestingly, high-performing students demonstrate somewhat counterintuitive behaviour— as conflicts escalate and GenAI becomes more insistent in its positions, these students paradoxically show a greater tendency toward positive engagement, including accepting and implementing GenAI's suggestions. However, this pattern reverses at extreme intensity levels, where all students show rejection tendencies toward GenAI's input, with this rejection effect being particularly pronounced among low-performing students.

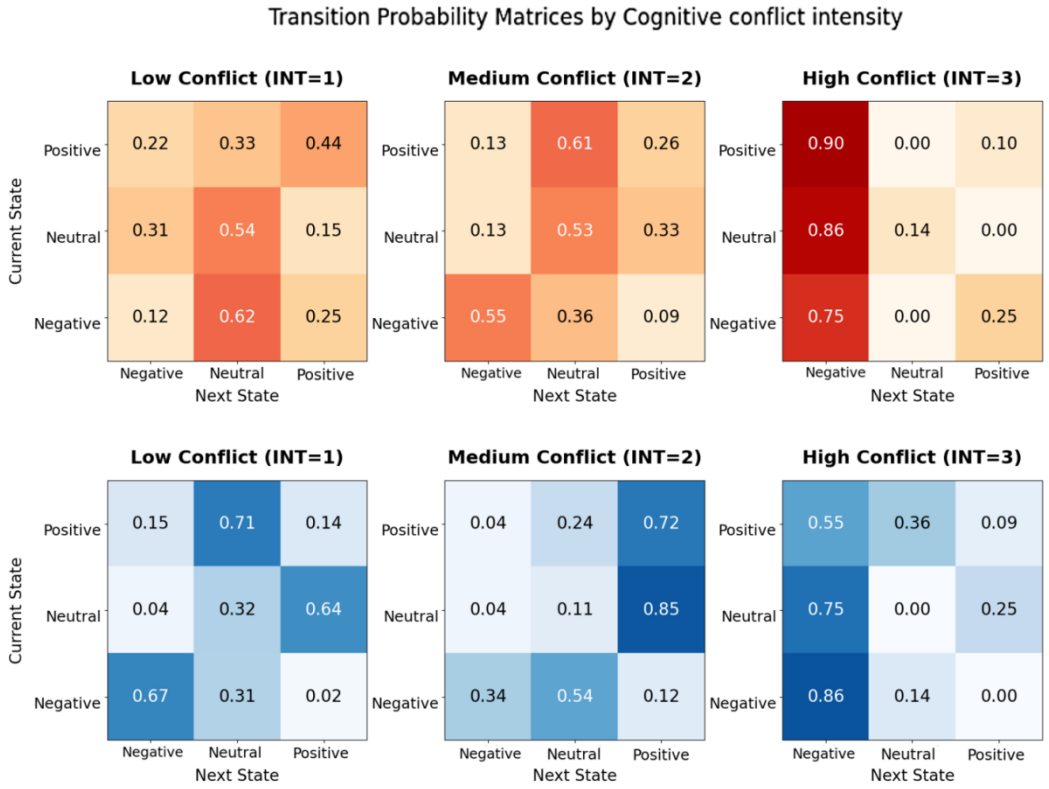


Figure 7. Transition probability diagram of different performance groups of students under different intensities, where red represents the low-performance group and blue depicts the high-performance group.

Table 3 shows the results of MLR using the covariate-dependent Markov method and contains some explanations of the parameters. The Pseudo R^2 model is distributed between 0.08 and 0.34. Although this study explores relationships and causal exploration rather than prediction and explanation, in general social sciences, a Pseudo R^2 of 0.1–0.3 is considered to have strong explanatory power (Smith and McKenna 2013). The key statistical indicators used are the Likelihood Ratio (LLR) p-value, which tests the model's overall significance, and the Odds Ratio (OR), which indicates the relative likelihood of a state transition occurring. In the high-performance group, the negative model was not significant (LLR $p = 0.274$), while the *neutral* and positive models were significant ($p < 0.01$). In the low-performance group, all models were significant (LLR $p < 0.05$), which generally showed that the overall impact of conflict intensity on state transition is universal.

4.3.1 Transfer From a Negative State

From the perspective of state transfer, the coefficients of INT for students in the low-performing group are −2.493 (OR = 0.083, $p < 0.001$) and −2.468 (OR = 0.085, $p = 0.001$), which have a significant negative effect: this means that an increase in cognitive conflict intensity will significantly reduce the possibility of low-performing students transferring from a negative state (the probability is reduced by 91.7% and 91.5%,

respectively), and low-performing students may choose to maintain their original state in the negative stage. This can be seen in the retrospective interview with a participant:

> *...GenAI always gives me some nonsense. I don't know how to use it. The conversation makes me more and more annoyed. It always talks nonsense. I don't want to spend my mind judging whether it is right or wrong. (Participant #16, low-performing group)*

High-performing students who transfer from a negative state to a *neutral* and *positive* state are 0.457 ($p = 0.262$) and 1.459 ($p = 0.223$), respectively, which are not significant. This shows that when high-performing students are in a negative state, the intensity of cognitive conflict has no significant effect on the probability of their transfer to other states. This also implicitly shows that high-performing students may have high adaptability, and the intensity of conflict will not significantly affect their initial negative behavioural decisions.

4.3.2 Transfer From a Neutral State

Their *neutral* state shifted to *neutral* (INT = −1.316, OR = 0.268, $p = 0.010$) and positive (INT = −1.301, OR = 0.272, $p = 0.043$), also showing a very significant negative effect. An increase in cognitive conflict intensity will significantly reduce the possibility of low-performing students shifting from a negative state (Each increase in conflict intensity by 1 unit, a 73.2% and 72.8% decrease, respectively, in odds). However, compared with the negative state, the increase in conflict intensity leads to a decrease in the probability of low-performing students shifting from the *neutral* state, which indirectly reflects that low-performing students will be more conservative when facing the uncertainty of cognitive conflict.

The students in the high-performing group also maintained this conclusion and finding. The high-performing students' *neutral* state shifted to the *neutral* (INT = −1.428, OR = 0.240, $p = 0.005$) and positive (INT = −1.193, OR = 0.303, $p = 0.022$) states, showing a significant negative effect. This means that an increase in conflict intensity significantly reduces the probability of high-performing students remaining *neutral* or turning to acceptance (Each increase in conflict intensity by 1 unit, a 76% and 69.7% decrease, respectively, in odds). This phenomenon suggests that when students are wavering in cognitive conflict, an increase in cognitive conflict will force students to significantly reduce their confidence and attitudes toward GenAI and will be more likely to induce rejection and confrontational behaviours. In this case, the retrospective description mentioned that:

> *...GenAI gave me an algorithm I had never seen before. I asked it several times, and it seemed to give me the correct explanation, but it took a long time to deduce. I was worried that if I made a mistake in such a long derivation, I might not be able to find it. To be on the safe side, I abandoned it... (Participant #7, high-performing group)*

4.3.3 Transfer From a Positive State

The low-performing students' positive state turned to *neutral* (INT = −2.034, OR = 0.131, p = 0.013), which showed a significant negative effect. It revealed that high-intensity conflict significantly inhibited their flexibility to transition from positive to neutral states. However, the positive state was not significant (p = 0.303). The effect of high-performing students' positive state turning to *neutral* was not significant (p = 0.121), but maintaining the positive state (INT = −3.999, OR = 0.018, p = 0.001) showed a significant and extremely strong negative effect. High conflict intensity almost completely inhibited high-performing students from remaining in the positive state (each increase in conflict intensity by 1 unit, a 98.2% decrease in odds).

Table 3. MLR results of different intensities.

Low-performing student groups									
Current state	Pseudo R^2	LLR p-value	Target state	β (INT)	SD	OR value	OR 95% CI	p	Significance
Negative	0.21	0	Neutral	−2.493	0.698	0.083	[0.021, 0.325]	0.000	***
			Positive	−2.468	0.737	0.085	[0.020, 0.359]	0.001	**
Neutral	0.11	0.01	Neutral	−1.316	0.511	0.268	[0.099, 0.729]	0.010	*
			Positive	−1.301	0.643	0.272	[0.077, 0.961]	0.043	*
Positive	0.16	0.01	Neutral	−2.034	0.821	0.131	[0.026, 0.654]	0.013	*
			Positive	−0.799	0.776	0.45	[0.099, 2.057]	0.303	
High-performing student groups									
Current state	Pseudo R^2	LLR p-value	Target state	β (INT)	SD	OR value	OR 95% CI	p	Significance
Negative	0.03	0.274	Neutral	0.457	0.408	1.579	[0.710, 3.512]	0.262	
			Positive	1.459	1.198	4.3	[0.411, 44.984]	0.223	
Neutral	0.08	0.006	Neutral	−1.428	0.507	0.24	[0.089, 0.648]	0.005	**
			Positive	−1.193	0.520	0.303	[0.109, 0.840]	0.022	*
Positive	0.34	0	Neutral	−1.765	1.138	0.171	[0.018, 1.592]	0.121	
			Positive	−3.999	1.152	0.018	[0.002, 0.175]	0.001	***

Note: Pseudo R^2: Similar to R^2 in linear regression, it indicates the proportion of variation explained by the model. LLR p-value: The p-value calculated by the likelihood ratio statistic, indicators for testing the overall significance of the model. β: Compared to the baseline state, the regression coefficient of the change in the logarithmic odds ratio for each unit increase in the INT. OR Value: Odds Ratio, compared to the baseline state, the ratio of the possible transition caused by the independent variable. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

5. Discussion

This study found that the intensity of cognitive conflicts is a key factor influencing students' learning states. As the intensity of conflicts increases, it affects the likelihood of students transitioning between cognitive conflict response states, suggesting that cognitive conflict plays a dynamic role in shaping students' affective and behavioural response with GenAI. There is a close bidirectional relationship between affective and behavioural responses and cognitive processes. Emotion and behaviour are not only the products of cognitive assessment but also, in turn, influence metacognitive strategies and restrict the allocation of cognitive resources (Ben-Zur 1999; Ramírez Arellano et al. 2018). We further expand on the existing educational phenomena and insight in the following sections:

5.1 Conflict Intensity and State Transition

The intensity of cognitive conflict has a significant impact on students' state transition. The results (**Table 3**) show that the intensity of cognitive conflict in this study exhibits a nonlinear regulatory mechanism. Overall, as the level of intensity increased, students' state changes exhibited a phased pattern, shifting from fluctuation (transitioning to a variety of different states) to inertia or convergence (maintaining the original state or transitioning uniformly to a negative response state). When cognitive conflict reaches a moderate intensity, students' state transitions increase significantly, while when cognitive conflict reaches a high level, students' state changes tend to be conservative. **Figure 7** shows that under the state of high-intensity cognitive conflict, the probability of both groups of subjects transitioning from non-negative states (neutral and positive states) to negative states reached the highest value, indicating that they tended to move away from accepting or tentative stances and toward rejecting or disengaging from GenAI's output.

It may reveal two scenarios. One is that a high-intensity state of cognitive conflict may lead to a tendency toward cognitive closure. Patterns such as avoiding ambiguity, reducing state transitions, and adhering to previous responses are all behavioural characteristics of this cognitive closure tendency (Webster and Kruglanski 1997). The second scenario is that high-intensity conflict continuously consumes an individual's cognitive resources. When available resources are insufficient to support further state assessment and adjustment, maintaining the existing state becomes the default choice with the least resistance, forming a tendency of passive cognitive closure.

From the perspective of cognitive dissonance theory, excessive conflict may exceed an individual's tolerance threshold (Harmon-Jones and Mills 1999). On an emotional level, this may manifest as the accumulation of frustration, anxiety, or resistance, causing students to emotionally withdraw from GenAI interactions. The solidification of this emotional state is manifested in behaviour as defensive responses such as reinforcing previous attitudes or halting further evaluations to alleviate psychological discomfort (Magnani 2022; Miller 1970). This state of imbalance may further weaken students'

self-regulation ability. When a large amount of cognitive resources is used to deal with emotional discomfort, the metacognitive resources that students use to monitor, evaluate, and adjust learning strategies decrease accordingly. This highlights the significance of cognitive resource management in the GenAI-assisted learning context. How to retain sufficient cognitive margin for students under high-intensity conflicts might be the key issue that instructional design needs to focus on in the GenAI-assisted learning environment.

This weakening is particularly worthy of attention in the GenAI-assisted learning context. In the process of encountering cognitive conflicts, critically evaluating the output of GenAI itself requires continuous cognitive investment. Although the framework of this study does not presuppose the epistemological authority of GenAI's output, students may spontaneously regard GenAI as an implicit cognitive authority in actual interactions. When students lack cognitive resources, GenAI's fluent and confident delivery may make them more receptive to AI suggestions rather than engaging in critical thinking or actively questioning its reliability.

Unlike traditional knowledge authorities, GenAI's authority does not stem from verifiable professional qualifications but from the superficial credibility of its output, and students may be inclined to attribute the discrepancy to their own mistakes rather than to the shortcomings of GenAI. When self-regulation ability is impaired due to cognitive dissonance, this tendency of authority obedience may be further strengthened. Precisely at the moment of high cognitive conflict, when students most need to maintain a critical distance, their ability to recognize the illusory output of GenAI may also decline simultaneously, and the risk of regarding incorrect or inaccurate GenAI output as reliable knowledge increases accordingly.

This study operationalizes cognitive conflict as the perceived gap between students' beliefs and GenAI outputs. This definition does not presuppose the correctness of GenAI outputs, nor does it control or verify their quality. This means that students' negative states may simultaneously include two distinct situations: one is the erroneous rejection of correct GenAI outputs under the pressure of cognitive authority, and the other is the correct identification and rejection of illusory GenAI outputs, the latter being precisely the manifestation of critical thinking.

5.2 Different Students' Responses to Cognitive Conflicts

The results show that students with different performances have differences in state transition. After evaluating the task results, it was found that students who achieved high performance in the task results demonstrated stronger state stability and were less likely to experience state transitions under cognitive conflicts. This model is compatible with two possible explanations.

Firstly, students who achieve high-performance results in task outcomes may possess a stronger sense of self-efficacy, enabling them to maintain a more stable response state when facing conflicts. Combining the concept of metacognitive masking, they may be able to actively filter out interfering information and maintain goal-oriented learning

behaviour in high-pressure situations (Ball et al. 2018), which is consistent with the description of skilled self-modulators in Winne's COPES (Conditions, Operations, Products, Evaluations, Standards) model (Winne 2017). From this perspective, the reduction in the number of state transitions may indicate that students have remained accepting and open before conflicts have been fully evaluated and have undergone a well-considered and controlled processing process. It is understood as a manifestation of careful judgement (critical thinking).

Secondly, however, a stable state may also reflect another situation. High-performing students have a relatively low perception of conflict in GenAI's output or a limited level of cognitive engagement with GenAI-generated content. In this case, a stable state does not necessarily stem from a stronger regulatory ability but may manifest as a relatively fixed cognitive stance or selective information processing mode, that is, to prioritize maintaining the existing response tendency without fully evaluating new information.

Students who achieve low performance in task results are more likely to turn to a negative state when the intensity of cognitive conflict increases. On the one hand, the increase in the tendency to turn negative may reflect the way some students respond to the emotional stress and cognitive load brought about by high-intensity conflicts (Norem 2008; Norem and Cantor 1986). In situations where conflicts are difficult to resolve quickly, individuals may tend to reduce cognitive load as well as the stress brought by uncertainty rather than continuously engaging in complex information processing procedures (Cho and Cho 2018). When this high-conflict scenario escalates, students may be more likely to reject GenAI output (Lambird and Mann 2006). As participant #16 shows, this phenomenon may manifest as an intensified sense of frustration, leading them to be reluctant to critically analyse the output results of GenAI. On the other hand, as noted in Section 5.1, some negative responses may also indicate a critical evaluation situation where students intentionally judge, analyse, and compare different schemes or viewpoints to avoid the false information brought by the GenAI hallucination.

Overall, the response patterns of both groups present interpretive complexity. Our results suggest that in cognitive conflicts, students may develop a tendency to avoid complex information or overly adhere to viewpoints that have not been fully evaluated. This warrants particular concern, because if some high-conflict situations persist without proper guidance, it may hinder the development of critical thinking in students in a GenAI-assisted learning environment. This obstacle is related to the cognitive authority effect discussed earlier. When critical assessment skills are impaired by intense conflicts, students may either over-accept GenAI outputs due to cognitive authority pressure or abandon the effective recognition of GenAI hallucinations due to resource depletion. Both of these situations indicate that acceptance or rejection at the behavioural level alone cannot fully reflect the quality of learning. An in-depth analysis of the reasoning process itself might be a more crucial entry point for future research.

5.3 Implications for Instructional Designers and Educators

This study reveals the complex effects of cognitive conflict on student responses and

highlights the importance of cognitive conflict management when learning with GenAI. GenAI systems could be designed to be sensitive to and actively manage the dynamics of cognitive conflict. By analysing linguistic cues and interaction data, the system can provide timely feedback to students and teachers regarding potential risks of cognitive conflict and offer supportive measures. For example, after a frustrating exchange, the system might prompt, 'Try a different topic. Once I receive more information, I might be able to provide you with a satisfactory answer'. This helps students break the negative feedback loop and regain their self-efficacy in learning, leading to improved task performance (Shen et al. 2013).

Considering the dynamic changes in response states among students with different performances, the system design might follow the principle of differentiated instruction to help different students solve their own interaction problems. For example, for students prone to unstable cognitive response states, metacognitive scaffolding could be provided, including encouraging them to establish their own independent thinking processes and providing encouraging feedback to help them build confidence in problem solving. Conversely, for high-performing students, when they become overly confident and attached to a particular viewpoint, the system design should encourage them to criticize the shortcomings of their own views.

Furthermore, educating students on how to make wiser judgements and handle conflicts when using GenAI could be considered an important part of developing their AI literacy and capabilities. To help students develop a deeper understanding of their own learning process and manage cognitive conflict, educators might consider proactively integrating the learning of metacognitive skills into relevant courses and systematically cultivating students' critical thinking and knowledge organization abilities in human-AI interactions (Liu et al. 2026). For example, before assigning a task, students can be asked to anticipate potential difficulties and plan actions to take if they feel confused. This may help students to adjust their learning strategies, potentially fostering engagement and motivation in GenAI-assisted learning experience (Chang et al. 2023).

6. Limitations

This study provides novel perspectives to explore cognitive conflicts in GenAI-assisted learning, while it also has a few methodological constraints. First, the exclusive focus on STEM-domain tasks may limit generalizability, as the interaction patterns of GenAI-assisted learning in social sciences or humanities may present different characteristics due to different disciplinary epistemological foundations. Second, although the Markov property has been statistically verified, the lack of longitudinal data across longer human-AI interaction cycles may underestimate the importance of cumulative effects, such as the students' experience and ability improvement in GenAI-assisted learning.

It is also worth noting that the overlap between hallucination and critical thinking represents an important interpretive challenge in this context. Furthermore, while our coding scheme can capture students' emotional and behavioural responses, it cannot distinguish the underlying reasoning and cognitive mechanisms that lead to negative reactions. If a student rejects GenAI's suggestion because they discovered a factual

error (an expression of critical thinking), or if a student rejects the suggestion because they feel frustrated or cognitively overwhelmed, both situations will be encoded as negative responses, but may have opposite effects on the quality of learning. As illustrated by the interview excerpt from Participant #7 in Section 4, some instances of negative response states appear to reflect deliberate evaluative judgement rather than mere frustration. Future research should develop more fine-grained coding schemes capable of distinguishing critical rejection from emotionally-driven rejection, which would allow for a more nuanced understanding of the role of critical thinking in human-AI interaction.

Finally, given the differences across individual qualities and learning environments, the cognitive conflict resolution model observed in this study may not be directly transferable to all student groups. The controlled laboratory setting of this study, while necessary for systematic data collection, may differ significantly from real classroom environments or self-directed informal learning and could not fully capture the affective stakes and ecological complexity of authentic classroom GenAI use: students interact with GenAI for extended periods, completing various tasks and potentially receiving varying levels of resource support, all of which may influence their responses to GenAI. Therefore, the specific transfer probabilities reported in this paper may not be directly generalizable to other student groups, subject backgrounds, or natural GenAI-assisted learning environments, and the generalizability of our findings to non-simulated learning environments needs to be treated with caution.

Future research may apply multi-modal data, such as electroencephalogram or galvanic skin response data, to strengthen the precise monitoring and measurement of cognitive conflicts, and adopt deep learning-based methods to better capture the nonlinear relationship of students' cognitive characteristics. In addition, comparative studies in the fields of STEM and humanities can help reveal the characteristics of cognitive conflict resolution models in different disciplines.

7. Conclusion

Managing cognitive conflicts becomes increasingly important in GenAI-assisted learning. This study innovatively proposes a covariate-dependent Markov chain model to understand how cognitive conflict intensity affects students' cognitive response state transitions during cognitive conflicts. We identified three cognitive response states: negative, neutral, and positive, and established three levels of cognitive conflict intensity. Our results show that the escalating cognitive conflict intensity significantly affects the probability of response state transitions, thereby gradually making students' existing response states more conservative. We also discussed the potential underlying reasons for the observed differences in response state transitions among students with different task performance levels when facing varying intensities of cognitive conflict. To our knowledge, this is the first study in the field of human-AI interaction to model student-GenAI interaction as a bidirectional temporal sequential process. By integrating cognitive conflict theory with dynamic state transition modelling, this study establishes a novel analytical framework and provides a new perspective for understanding the

sequentiality and temporal dependence of human-computer interaction in GenAI-assisted learning.

Author Contributions

Yiming Taclis Luo: conceptualization, methodology, software, data curation, investigation, validation, formal analysis, writing – original draft, visualization. Ting Liu: investigation, validation, formal analysis, data curation, visualization. Patrick Pang: funding acquisition, project administration, resources, writing – review and editing, supervision. Xiao Hu: supervision, writing – review and editing.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

1 https://www.kaggle.com/datasets/markmedhat/student-scores.

References

Ball, L., E. Threadgold, A. Solowiej, and J. Marsh. 2018. “Can Intrinsic and Extrinsic Metacognitive Cues Shield Against Distraction in Problem Solving?” *Journal of Cognition 1*: 15. https://doi.org/10.5334/joc.9.

Ben-Zur, H. 1999. “The Effectiveness of Coping Meta-Strategies: Perceived Eficiency, Emotional Correlates and Cognitive Performance.” *Personality and Individual Differences 26*, no. 5: 923–939. https://doi.org/10.1016/s0191-8869(98)00198-6.

Berlyne, D. 1970. “Children's Reasoning and Thinking.” In *Carmichael's Manual of Child Psychology*, *edited by P. H. Mussen, vol. 1*, 939–981.

Chan, C., J. Burtis, and C. Bereiter. 1997. “Knowledge Building as a Mediator of Conflict in Conceptual Change.” *Cognition and Instruction 15*, no. 1: 1–40. https://doi.org/10.1207/s1532690xci1501_1.

Chang, D., M. P.-C. Lin, S. Hajian, and Q. Wang. 2023. “Educational Design Principles of Using AI Chatbot That Supports Self-Regulated Learning in Education: Goal Setting, Feedback, and Personalization.” *Sustainability 15*: 12921. https://doi.org/10.3390/su151712921.

Chen, Z., S. Cross, and B. Rienties. 2024. “Empowering Assessors in Providing Quality Feedback With GenAI Assistance: A Preliminary Exploration.” In Technology in Education. Digital and Intelligent Education (Communications in Computer and Information Science, Vol. 2191), edited by L.-K. Lee, P. Poulova, K. T. Chui, M. Černá, F. L. Wang, and S. K. S. Cheung, 134–148. Springer.

Cho, C., and T. Cho. 2018. “On Averting Negative Emotion: Remedying the Impact of Shifting Expectations.” *Frontiers in Psychology 9*: 2121. https://doi.org/10.3389/fpsyg.2018.02121.

Dai, Y. 2024. “Why Students Use or Not Use Generative AI: Student Conceptions, Concerns, and Implications for Engineering Education.” *Digital Engineering 4*: 100019. https://doi.org/10.1016/j.dte.2024.100019.

Dehais, F., M. Causse, F. Vachon, and S. Tremblay. 2012. “Cognitive Conflict in Human-Automation Interactions: A Psychophysiological Study.” *Applied Ergonomics 43*: 588–595. https://doi.org/10.1016/j.apergo.2011.09.004.

Essel, H., D. Vlachopoulos, A. Essuman, and J. Amankwa. 2024. “ChatGPT Effects on Cognitive Skills of Undergraduate Students: Receiving Instant Responses From AI-Based Conversational Large Language Models (LLMs).” *Computers and Education: Artificial Intelligence 6*: 100198. https://doi.org/10.1016/j.caeai.2023.100198.

Gabbiadini, A., D. Ognibene, C. Baldissarri, and A. Manfredi. 2025. “The Emotional Impact of Generative AI: Negative Emotions and Perception of Threat.” *Behaviour & Information Technology 44*, no. 4: 676–693. https://doi.org/10.1080/0144929X.2024.2333933.

Gu, J., and Z. Yan. 2025. “Effects of GenAI Interventions on Student Academic Performance: A Meta-Analysis.” *Journal of Educational Computing Research 63*: 1460–1492. https://doi.org/10.1177/07356331251349620.

Häggström, O. 2002. *Finite Markov Chains and Algorithmic Applications*. Vol. 52. Cambridge University Press.

Harmon-Jones, E., and J. Mills. 1999. “An Introduction to Cognitive Dissonance Theory and an Overview of Current Perspectives on the Theory.”

Hewson, M. G. A. B. 1988. “The Ecological Context of Knowledge: Implications for Learning Science in Developing Countries.” *Journal of Curriculum Studies 20*, no. 4: 317–326. https://doi.org/10.1080/0022027880200402.

Hyytinen, H., K. Holma, A. Toom, R. Shavelson, and S. Lindblom-Ylänne. 2014. “The Complex Relationship Between Students' Critical Thinking and Epistemological Beliefs in the Context of Problem Solving.” *Frontline Learning Research 6*: 1–25. https://doi.org/10.14786/flr.v2i4.124.

Iran-Nejad, A. 1990. “Active and Dynamic Self-Regulation of Learning Processes.” *Review of Educational Research 60*, no. 4: 573–602. https://doi.org/10.3102/00346543060004573.

Jaboob, M., M. Hazaimeh, and A. Al-Ansi. 2024. “Integration of Generative AI Techniques and Applications in Student Behavior and Cognitive Achievement in Arab Higher Education.” *International Journal of Human-Computer Interaction 41*: 1–14. https://doi.org/10.1080/10447318.2023.2300016.

Johnson, D. W., and R. T. Johnson. 2009. “Energizing Learning: The Instructional Power of Conflict.” *Educational Researcher 38*, no. 1: 37–51. https://doi.org/10.3102/0013189X08330540.

Kang, S., L. C. Scharmann, and T. Noh. 2004. “Reexamining the Role of Cognitive Conflict in Science Concept Learning.” *Research in Science Education 34*: 71–96. https://doi.org/10.1023/B:RISE.0000021001.77568.b3.

Lambird, K. H., and T. Mann. 2006. “When Do Ego Threats Lead to Self-Regulation Failure? Negative Consequences of Defensive High Self-Esteem.” *Personality and Social Psychology Bulletin 32*, no. 9: 1177–1187. https://doi.org/10.1177/0146167206289408.

Lee, G., J. Kwon, S. S. Park, J. W. Kim, H. G. Kwon, and H. K. Park. 2003. “Development of an Instrument for Measuring Cognitive Conflict in Secondary-Level Science Classes.” *Journal of Research in Science Teaching 40*, no. 6: 585–603. https://doi.org/10.1002/tea.10099.

Lee, G., S.-S. Park, J.-W. Kim, H.-G. Kwon, J.-S. Kwon, and H.-K. Park. 1999. “The Development of an Instrument for the Measuring Students' Cognitive Conflict Levels.”

Lee, G., and J. Yi. 2013. “Where Cognitive Conflict Arises From?: The Structure of Creating Cognitive Conflict.” *International Journal of Science and Mathematics Education 11*: 601–623. https://doi.org/10.1007/s10763-012-9356-x.

Li, H., F. Yang, and J. Liu. 2026. “Task Complexity and AI Dependency Among College Students: The Mediating Roles of Cognitive Load, Future Anxiety, and Task Motivation.” *BMC Psychology 14*: 552. https://doi.org/10.1186/s40359-026-04204-2.

Li, X., G. Chen, and C. Yang. 2021. “How Cognitive Conflict Affects Judgments of Learning: Evaluating the Contributions of Processing Fluency and Metamemory Beliefs.” *Memory & Cognition 49*, no. 5: 912–922. https://doi.org/10.3758/s13421-021-01143-8.

Limón, M. 2001. “On the Cognitive Conflict as an Instructional Strategy for Conceptual Change: A Critical Appraisal.” *Learning and Instruction 11*, no. 4: 357–380. https://doi.org/10.1016/S0959-4752(00)00037-2.

Liu, H., T. Niu, C. Shengyan, P. Pang, T. Liu, and Y. Taclis Luo. 2026. “Toward Sustainable Aesthetic Education: Exploring the Impact of GenAl Collaboration on Students' Critical Thinking Disposition.” *Frontiers in Psychology 17: 1852109*. https://doi.org/10.3389/fpsyg.2026.1852109.

Lu, S., I. Bigoulaeva, R. Sachdeva, H. Tayyar Madabushi, and I. Gurevych. 2024. *“Are Emergent Abilities in Large Language Models Just in-Context Learning?*.” Paper Presented at Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers).

Luo, Y., T. Liu, P. C.-I. Pang, D. McKay, S. Chang, and G. Buchanan. 2026a. “Inquiry-Based Learning Patterns in Large Language Model-Driven Learning Environments: An Exploratory Study From Bloom's Perspective.” *Australasian Journal of Educational Technology 42*, no. 1: 38–57. https://doi.org/10.14742/ajet.10773.

Luo, Y., P. C.-I. Pang, and S. Chang. 2025. “Enhancing Exploratory Learning Through Exploratory Search With the Emergence of Large Language Models.” Paper Presented at *Proceedings of the 58th Hawaii International Conference on System Sciences*.

Luo, Y. T., T. Liu, P. Pang, and H. Y. Kan. 2026. “Decoding Dynamic Emotional Valence in GenAI Interactions: Insights From Covariate-Dependent Markov Chains [Original Research].” *Frontiers in Psychology 17: 1783364*. https://doi.org/10.3389/fpsyg.2026.1783364.

Luo, Y. T., T. Liu, P. Pang, D. McKay, S. Chang, and G. Buchanan. 2026b. “Interpreting Interaction Patterns and Cognitive Strategies in LLM-Supported Exploratory Learning: A Mixed-Methods Analysis Using the DOK Framework.” *Information 17*, no. 3: 288. https://doi.org/10.3390/info17030288.

Luo, Y. T., T. Liu, P. C.-I. Pang, Z. Wang, and K. I. Chan. 2025. “Exploring Information Interaction Preferences in an LLM-Assisted Learning Environment With a Topic Modeling Framework.” *Applied Sciences 15*, no. 13: 7515. https://doi.org/10.3390/app15137515.

Magnani, L. 2022. “Human Abductive Cognition Vindicated: Computational Locked Strategies, Dissipative Brains, and Eco-Cognitive Openness.” *Philosophies 7*: 15. https://doi.org/10.3390/philosophies7010015.

McKay, D., S. Makri, M. Gutierrez-Lopez, et al. 2024. “I'm the Same, I'm the Same, I'm Trying to Change: Investigating the Role of Human Information Behavior in View Change.” *Journal of the*

Association for Information Science and Technology 75: 844–858. https://doi.org/10.1002/asi.24885.

Miller, L. W. 1970. *Conflict: Facilitator or Inhibitor of Creative Performance*. University of Oklahoma.

Nguyen, A., Y. Hong, B. Dang, and X. Huang. 2024. "Human-AI Collaboration Patterns in AI-Assisted Academic Writing." *Studies in Higher Education 49*: 847–864. https://doi.org/10.1080/03075079.2024.2323593.

Niu, T., T. Liu, Y. T. Luo, P. C.-I. Pang, S. Huang, and A. Xiang. 2025. "Decoding Student Cognitive Abilities: A Comparative Study of Explainable AI Algorithms in Educational Data Mining." *Scientific Reports 15*, no. 1: 26862. https://doi.org/10.1038/s41598-025-12514-5.

Norem, J. K. 2008. "Defensive Pessimism, Anxiety, and the Complexity of Evaluating Self-Regulation." *Social and Personality Psychology Compass* 2, *no.* 1: 121–134. https://doi.org/10.1111/j.1751-9004.2007.00053.x.

Norem, J. K., and N. Cantor. 1986. "Defensive Pessimism: Harnessing Anxiety as Motivation." *Journal of Personality and Social Psychology 51*, no. 6: 1208–1217. https://doi.org/10.1037/0022-3514.51.6.1208.

Pérez-Jorge, D., M. Boutaba-Alehyan, A. I. González-Contreras, and I. Pérez-Pérez. 2025. "Examining the Effects of Academic Stress on Student Well-Being in Higher Education." *Humanities & Social Sciences Communications 12*, no. 1: 449. https://doi.org/10.1057/s41599-025-04698-y.

Posner, G. J., K. A. Strike, P. W. Hewson, and W. A. Gertzog. 1982. "Accommodation of a Scientific Conception: Toward a Theory of Conceptual Change." *Science Education 66*, no. 2: 211–227. https://doi.org/10.1002/sce.3730660207.

Ramírez Arellano, A., J. Bory-Reyes, and L. Hernandez Simon. 2018. "Emotions, Motivation, Cognitive–Metacognitive Strategies, and Behavior as Predictors of Learning Performance in Blended Learning." *Journal of Educational Computing Research 57*: 491–512. https://doi.org/10.1177/0735633117753935.

Rodman, A., and E. J. Topol. 2025. "Is Generative Artificial Intelligence Capable of Clinical Reasoning?" *Lancet 405*, no. 10480: 689. https://doi.org/10.1016/S0140-6736(25)00348-4.

Roth, W. M., and A. Jornet. 2013. "Situated Cognition." *Wiley Interdisciplinary Reviews: Cognitive Science* 4, *no.* 5: 463–478. https://doi.org/10.1002/wcs.1242.

Schulz-Schaeffer, I. 2025. "Why Generative AI Is Different From Designed Technology Regarding Task-Relatedness, User Interaction, and Agency." *Big Data & Society 12*, no. 3: 1–13. https://doi.org/10.1177/20539517251367452.

Shen, D., M.-H. Cho, C.-L. Tsai, and R. Marra. 2013. "Unpacking Online Learning Experiences: Online Learning Self-Efficacy and Learning Satisfaction." *Internet and Higher Education 19*: 10–17. https://doi.org/10.1016/j.iheduc.2013.04.001.

Smedslund, J. 1961. "The Acquisition of Conservation of Substance and Weight in Children: II. External Reinforcement of Conservation of Weight and of the Operations of Addition and Subtraction." *Scandinavian Journal of Psychology* 2, *no.* 1: 71–84. https://doi.org/10.1111/j.1467-9450.1961.tb01223.x.

Smith, T. J., and C. M. McKenna. 2013. "A Comparison of Logistic Regression Pseudo R2 Indices." *Multiple Linear Regression Viewpoints 39*, no. 2: 17–26.

Stavy, R., and B. Berkovitz. 1980. "Cognitive Conflict as a Basis for Teaching Quantitative Aspects of the Concept of Temperature." *Science Education 64*, no. 5: 679–692. https://doi.org/10.1002/sce.3730640514.

Suchman, L. A. 1987. *Plans and Situated Actions: The Problem of Human-Machine Communication*. Cambridge university press.

Tan, J., S. Wu, L. Wu, and S. Ma. 2025. "Cognitive Conflicts in Collaborative Programming and Their Impact on Computational Concept Acquisition." *Learning and Instruction 98*: 102151. https://doi.org/10.1016/j.learninstruc.2025.102151.

Todorova, G., K. Goh, and L. Weingart. 2021. "The Effects of Conflict Type and Conflict Expression Intensity on Conflict Management." *International Journal of Conflict Management 33*: 245–272. https://doi.org/10.1108/IJCMA-03-2021-0042.

Tsai, S.-C. 2025. "Online EFL Business Writing With GenAI-Generated Templates: Students' Performance and Perceptions." *Australasian Journal of Educational Technology 41*: 82–97. https://doi.org/10.14742/ajet.10743.

Vandenplas-Holper, C. 1996. "Intraindividual and Interindividual Cognitive Conflict, Related Variables and Relations With Cognitive Development." *Schweizerische Zeitschrift Für Psychologie 55*, no. 2: 161.

Wang, F., N. Li, A. C. K. Cheung, and G. K. W. Wong. 2025. "In GenAI We Trust: An Investigation of University Students' Reliance on and Resistance to Generative AI in Language Learning." *International Journal of Educational Technology in Higher Education 22*, no. 1: 59. https://doi.org/10.1186/s41239-025-00547-9.

Wang, S., Y. Wang, and M. Solhi. 2025. "Teacher-Student Interpersonal Behaviours and GenAI Feedback on Students' Achievement Emotions in EFL Writing: An Intervention Study." *European Journal of Education 61*: 1–14. https://doi.org/10.1111/ejed.70395.

Wang, Y., and D. Stein. 2021. "Effects of Online Teaching Presence on Students' Cognitive Conflict and Engagement." *Distance Education 42*: 1–20. https://doi.org/10.1080/01587919.2021.1987837.

Webster, D. M., and A. W. Kruglanski. 1997. "Cognitive and Social Consequences of the Need for Cognitive Closure." *European Review of Social Psychology* 8, *no.* 1: 133–173. https://doi.org/10.1080/14792779643000100.

Winne, P. H. 2017. "Cognition and Metacognition Within Self-Regulated Learning." In *Handbook of Self-Regulation of Learning and Performance*, 36–48. Routledge.

Wood, D., and S. Moss. 2024. "Evaluating the Impact of Students' Generative AI Use in Educational Contexts." *Journal of Research in Innovative Teaching & Learning 17*: 152–167. https://doi.org/10.1108/JRIT-06-2024-0151.

Wu, Y. T., and C. C. Tsai. 2011. "High School Students' Informal Reasoning Regarding a Socio-Scientific Issue, With Relation to Scientific Epistemological Beliefs and Cognitive Structures." *International Journal of Science Education 33*, no. 3: 371–400. https://doi.org/10.1080/09500690903505661.

Yan, L., S. Greiff, Z. Teuber, and D. Gasevic. 2024. "Promises and Challenges of Generative Artificial Intelligence for Human Learning." *Nature Human Behaviour 8*: 1839–1850. https://doi.org/10.1038/s41562-024-02004-5.

Yang, X., and M. Zhang. 2024. "Genai Distortion: The Effect of Genai Fluency and Positive Affect." *Preprint, arXiv:2404.17822*.

Zhu, Y., Q. Liu, and L. Zhao. 2025. "Exploring the Impact of Generative Artificial Intelligence on Students' Learning Outcomes: A Meta-Analysis." *Education and Information Technologies 30*: 16211–16239. https://doi.org/10.1007/s10639-025-13420-z.

Zuo, S., Q. Huang, and C. Qi. 2024. “The Relationship Between Cognitive Activation and Mathematics Achievement: Mediating Roles of Self-Efficacy and Mathematics Anxiety.” *Current Psychology 43*: 30794–30805. https://doi.org/10.1007/s12144-024-06700-3.

Appendix A

Students were assigned a data science exploratory task. The researchers provided students with a public dataset related to educational academic performance from Kaggle[1] (The data set was adjusted according to the actual situation), which included some students' grades and personal characteristics. The researchers made some modifications to the values and characteristics of these data to control the difficulty of academic writing. Students were asked to explore the potential insights in this educational dataset. At the same time, they were required to organize their insights into standardized academic papers with a certain format. The researchers informed the students that they would use a designated GenAI model to assist in the exploration and asked them to organize these findings. The specific requirements were presented again in written form as follows:

Task: The educational system is increasingly recognising the importance of data in improving student performance. By analysing various student characteristics, such as demographics, study habits, educators and institutions, we can develop strategies to foster a more personalised and effective learning environment. We will provide a relevant data set containing key variables. Please complete a 1000 or 2000-word essay by asking questions to the GenAI tool. Please complete the data of the essay according to the table content at the bottom of the document.

Please pay attention to the selection of the topic of the essay, such as innovation, and so forth, as well as the integrity of the structure and the logical coherence of the essay. The following data can be presented in the content of the essay through tables, pictures, and so forth. Please pay attention to checking the logic of the content during the generation process of the GenAI tool.

Table A1. Marking rubric.

Assessed areas	Excellent (4)	Good (3)	Fair (2)	Poor (1)
Content	The selected topic is well-suited to the characteristics of the dataset, with clear and concise perspectives that effectively extract and analyse the features of the original dataset, leading to an outstanding understanding.	The selected topic is reasonably aligned with the characteristics of the dataset, presenting clear viewpoints that appropriately correspond to the features of the original dataset, facilitating relevant extraction and analysis, and resulting in a good understanding.	The selected topic shows a moderate alignment with the characteristics of the dataset, offering relatively clear viewpoints that somewhat correspond to the features of the original dataset, enabling adequate extraction and analysis, and yielding a satisfactory understanding.	The selected topic is not entirely consistent with the characteristics of the dataset, with subpar viewpoints that fail to adequately correspond to the features of the original dataset, thereby hindering effective extraction and analysis and resulting in limited understanding.
Analysis	A comprehensive range of quantitative data analysis methods was employed, complemented by various graphical representations to effectively support the arguments presented.	A selection of quantitative data analysis methods was utilized, along with graphical representations, to provide support for the arguments.	Quantitative data analysis methods were used, supplemented by figures or tables, to offer a degree of support for the arguments.	No quantitative data analysis methods were employed, nor were any graphical representations used to display the data analysis results, resulting in a lack of support for the arguments.
Organization & Structure	Presents a well-structured essay with a clear introduction, body, and conclusion. Transitions are used effectively to connect ideas and paragraphs.	Presents a well-structured essay with a clear introduction, body, and conclusion. Transitions are used somewhat effectively to connect ideas and paragraphs.	Presents a fairly structured essay with a clear introduction, body, and conclusion. Transitions are used somewhat effectively to connect ideas and paragraphs.	Poorly structured essay. Transitions are not used effectively to connect ideas and paragraphs.

Assessed areas	Excellent (4)	Good (3)	Fair (2)	Poor (1)
Quality of writing	Good writing, with only a few minor errors. Sentences are well-constructed, with correct grammar and punctuation. Suitable for a professional audience.	Fair writing quality or good writing, but a few incorrect grammar and/ or punctuation. Style is not suitable for a professional audience.	Fair writing quality, but has many errors.	Poor writing quality with a significant number of errors.
Word limit & Referencing	Writing is within the word limit. Able to insert references correctly.	Writing may be slightly outside of the word limit. Able to insert references relatively correctly.	Writing may be slightly outside of the word limit. Some attempts at referencing, but with some noticeable errors. References can be inserted, but the format does not conform to the specification.	Writing is significantly over or under the word limit. Missing references.