Investigating the Role of Chatbots in Facilitating Learning Design

Shan Tang[1], Jie Shen[1], Jionghao Lin[1] and Nancy W. Y. Law[1,*]

[1]*The University of Hong Kong, Hong Kong, China*

Abstract

Learning design is a core part of teachers' work because it translates learning goals into coherent sequences of activities, resources, and assessments. Existing platforms such as Learning Design Studio (LDS) support teachers in systematically authoring and revising learning designs, which may also embed Generative Artificial Intelligence (GenAI) chatbots to support teacher–AI collaboration. GenAI such as ChatGPT can provide on-demand, context-sensitive suggestions during design, but how to preserve teacher agency and design accountability with its assistance remains a key challenge. This study investigates how Masters level students in a learning design course interact with a GPT-based chatbot, the LDFacilitator (LDF) embedded in the Learning Design Studio while completing learning design tasks. Building on an established learning design scaffolding framework, we developed a coding scheme to characterize conversational moves and theme transitions in student–chatbot dialogues. The scheme was then used to code a novice learning designers' dialogs with LDF as they conducted their design sessions on LDS identify the sequential structure of the human-AI interactions as theme-transition patterns over time. Our analysis reveals recurring trajectories linking problem framing, activity specification, assessment alignment, and feasibility constraints, as well as bottlenecks where students repeatedly seek clarification or validation. These findings inform the design of GenAI-supported learning design environments that scaffold productive design reasoning while maintaining teacher agency and accountability.

Keywords

Generative AI, Learning Design, Teacher-AI Interaction

1. Introduction

Learning design is a core part of teachers' work because it translates learning goals into coherent sequences of learning tasks and accompanying learning resources, and assessments. While modern technology allows instructors more flexibility in customizing the learning design, they still take responsibility for making increasingly numerous learning design decisions across various levels ranging from the selection of digital platforms and overarching pedagogical approaches to the planning of details such as assignment deadline setting, the number of assessment attempts permitted, and the choice of different types of activities [1]. This has reinforced the paradigm of teaching as design work, emphasizing that instructional effectiveness relies not only on knowledge transmission but also on the quality of the designed learning experiences [2, 3]. To support the design work, recent studies have developed frameworks and learning design systems to enable teachers to externalize designs as editable artifacts for reflection and iteration. For example, the Learning Design Studio (LDS) [4] based on a multilevel design framework have been provided to help teachers make design decisions across levels of granularity to ensure alignment among goals, learning tasks, and assessment choices [5].

The widespread availability of GenAI has opened up the possibility for educators to create more effective learning experiences. Emerging studies have suggested that chatbot-based GenAI assistants can provide educators with support in different facets of teachers' design work including designing lesson plans and learning tasks [6, 7, 8, 9]. However, the effectiveness of these assistants depends strongly on how teachers prompt, evaluate, and integrate AI suggestions into their own pedagogical reasoning. This

Joint Proceedings of LAK 2026 Workshops, co-located with the 16th International Conference on Learning Analytics and Knowledge (LAK 2026), Bergen, Norway, April 27 – May 1, 2026

*Corresponding author.
shantang0628@gmail.com (S. Tang); jieshen2024@connect.hku.hk (J. Shen); jionghao@hku.hk (J. Lin); nlaw@hku.hk (N. W. Y. Law)

presents a major challenge of how teachers could preserve their agency and maintain accountability while effectively leveraging AI-generated advice for which they take ultimate responsibility.

Despite the growing interests in GenAI-supported learning design, there is still a lack of research exploring the interaction patterns between learning designers, particularly novice designers, and GPT-based assistants in their design process. The framework of dialogic scaffolding offers a systematic way to characterize how support is mediated through interaction and can be adapted to analyze teacher–chatbot discourse in the learning design context [10].

This study investigates the interaction patterns between students in a Masters level course on learnig design and a GenAI-based chatbot during the learning design process. Building on the learning design framework underpinning LDS, we developed a coding scheme to characterize interaction moves and theme transitions found in student-chatbot dialogues, with the goal of identifying whether and how the dialogic interactions scaffolded novice learning designers in their design practice. The research questions guiding this study are: (1) What themes emerge during the interaction between the students and the chatbot? (2) How do these themes evolve during the interaction?

2. METHODS

2.1. Research context and data collection

A preliminary study was conducted with five novice learning designers taking a Masters level course on Learning Design and Technology. Within the course, participants were encouraged to use a web-based learning design environment (LDS) with an embedded GenAI-based chatbot (LDF) to create and revise learning designs. From a cohort of 24 students, these five students were purposefully selected based on their extended dialogues with the LDF chatbot. The selection criteria were to ensure a rich source of data for investigating theme transitions among students who were highly engaged with the chatbot and thus likely to perceive the dialogue as beneficial to their design process. Two data streams were obtained from the environment including the timestamped interaction logs from both the LDS platform and the LDF chatbot. The study was approved by the Institutional Human Ethics Committee and all students taking the course gave consent for the use of all their online learning data for the study. After de-identification, the corpus comprised 1378 student (designer)–chatbot interactions.

2.2. Designer-AI Conversational Theme Annotation

We developed a coding scheme using a grounded theory [11] to capture the conversational themes emerging from participant utterances throughout their interactions with the GenAI-based chatbot. Derived from the multilevel learning design framework [5] and subsequently adapted to our contextual learning design tasks, the coding scheme adopted a two-level hierarchy (Table 1). Level 1 codes captured the key dimensions of novice learning designers' pedagogical reasoning while Level 2 codes elaborated more specific aspects within each dimension. In this study, exclusive coding was applied, meaning that each participant's response was coded only with one code (encompassing codes for both levels) which indicated its primary theme. The codebook was then adopted by two coders who held master's degrees in education to code 5% of the sampled dialog data (60 dialog turns). They coded all responses independently. Inter-rater reliability was assessed using Cohen's kappa and indicated high agreement ($\kappa = 0.92$). The responses with different codes were resolved by discussions between the two coders.

2.3. Data Analysis

Markov chain transition pattern analysis was employed to characterize how conversational themes evolved over time during each student's interaction with the chatbot. We treated each Level 1 theme label as a conversational state and modeled the sequence of coded student turns as a first-order process in which the next theme depends on the immediately preceding theme. For each student, we counted theme-to-theme transitions between consecutive coded turns and converted these counts into transition probabilities, then combined transition counts across all five students to derive an overall transition profile. We visualized the resulting transitions as a directed state diagram, where thicker arrows indicate more likely transitions, and used this visualization to identify the most common theme-transition pathways.

Table 1
Codebook for themes during the interaction

First Level Code	Second Level Code
Off-topic	Greeting
Navigation	Open up, Request for LDS navigation, Giving LDS navigation, Request for LD access, Request for more information
Course information	Request for learning context, Advice on learning context, Request for course title, Giving course title advice, Background information
Learning design triangle (LDT)	Request for LDT concept, Explanation of LDT concept, Request for LDT sequence, Advice on LDT sequence
Intended learning outcome (ILO)	Request for ILO definition, Advice on ILO definition, Request for ILO advice, Advice on ILO, Request for ILO evaluation, Evaluation on ILO, Request the alignment with Bloom's taxonomy, Advice on the alignment with Bloom's taxonomy, Request for advice on ILO categorization, Advice on ILO different categories
Disciplinary Practice (DP)	Request for DP definition, Giving DP definition, Request for definition of a certain DP, Giving definition of a certain DP, Request for DP advice, Advice on a certain DP, Request for role-setting, Advice on role-setting, Request for DP workflow, Advice on workflow, Request for DP evaluation, Evaluation on DP
Pedagogical approach (PA)	Request for PA definition, Giving PA definition, Request for definition of a certain PA, Giving definition of a certain PA, Request for PA advice, Advice on a certain PA, Request for the definition of pedagogical foci, Giving the definition of pedagogical foci, Request for pedagogical foci, Advice on pedagogical foci, Request for PA evaluation, Advice on PA evaluation, Request for other pedagogical information, Giving other pedagogical information, Request for PA resource, Giving PA resource guidance
Curriculum Components (CC)	Request for CC advice, Advice on a certain CC, Request for CC evaluation, Advice on CC evaluation
Task	Request for a task advice, Advice on task, Request for task evaluation, Evaluation on a task
Patterns	Request for the definition of patterns, Providing the definition of patterns
Learning analytics	Request for advice on learning analytics questions

3. RESULTS

3.1. Theme transitions

Figure 1 presents the aggregated theme-transition network across all coded dialogues, showing how participants moved between learning design themes over time. The graph indicates a structured dialogic flow in which several themes tend to be persistently revisited in consecutive turns, while others often serve as bridges that connect different themes in the design process. Intended Learning Outcome shows the strongest within-theme persistence, with a self-transition probability of 0.84, suggesting that once participants begin articulating or refining outcomes, they often sustain focused exploration on this theme. Pedagogical Approach also shows high persistence with a self-transition probability of 0.71, indicating extended reasoning around how to approach and structure students' engagement in the learning process. Curriculum Components show moderate persistence with a self-transition probability of 0.50, which is consistent with iterative elaboration of what should be included in the design before moving to implementation details.

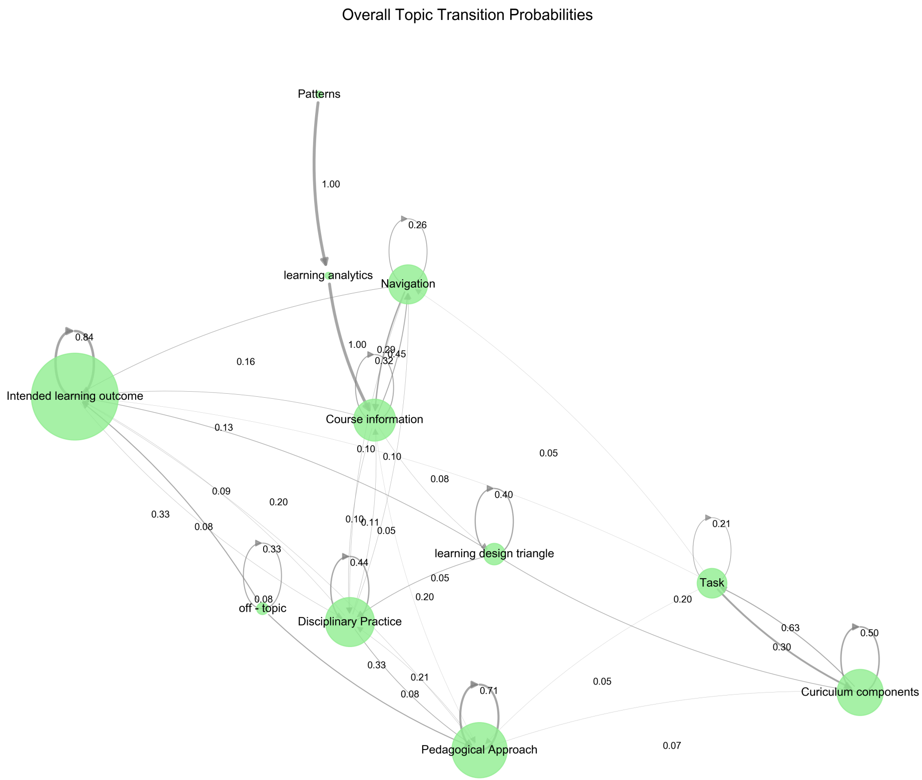

Figure 1: Overall theme Transition

Beyond persistence, the most informative patterns are the directional transitions that reflect how participants translate pedagogical intent into actionable designs. Curriculum Components transitions to Task with a probability of 0.63, indicating a common progression from specifying curriculum elements toward operationalizing those elements as concrete tasks. This pathway aligns with a key learning design move from "what students should work on" as a general orientation to "what students will do", which often requires additional design reasoning about task format, sequencing, and feasibility. Intended Learning Outcomes also connects to multiple other themes, functioning as a hub that anchors subsequent design moves. This distribution pattern suggests that participants repeatedly returned to outcomes to justify or recalibrate decisions about pedagogy, disciplinary practice, and task structure, which is consistent with the need for alignment check in outcome-based learning design practice.

The transition network also highlights themes that appear to support the management of design constraints and tool-mediated work. Transitions involving Course Information and Navigation indicate that participants frequently moved between substantive design reasoning and context-setting or platform-oriented actions. From a learning design perspective, these shifts are meaningful because they reveal when designers need to reconcile abstract design ideas with situational constraints, such as the learning context, course framing, or what the platform affords. Patterns operate as a meta-level theme in which participants ask about reusable design knowledge, and it shows a consistent pathway into framework-oriented discussion, which suggests that pattern-related prompts may prime participants to seek more structured conceptual guidance before returning to design decisions.

Figure 2 (blue, User 1078) illustrates a participant-level example for the student with the longest dialogue, showing how the overall structure can manifest in an individual design process. Intended Learning Outcome again shows strong persistence with a self-transition probability of 0.84, indicating sustained attention to outcome formulation and refinement. Pedagogical Approach has a self-transition probability of 0.67, and Disciplinary Practice has a self-transition probability of 0.55, suggesting that this student repeatedly worked on how to teach and what domain practices to emphasise, rather than treating these decisions as one-off choices. The graph also shows tight coupling between Curriculum Components and Task, with frequent reciprocal movement, which is characteristic of iterative design: the student alternated between specifying curriculum elements and revising the tasks that enact them, likely to improve coherence and practicality.

Taken together, the transition patterns provide learning design insights into how novice designers use a chatbot to move through alignment work. High persistence on Intended Learning Outcome and Pedagogical Approach suggests that participants used the interaction space for iterative clarification, refinement, and validation of core design intent, rather than only requesting surface-level suggestions. Strong transitions from Curriculum Components to Task indicate that the dialogue supported the critical "enactment step", where curricular ideas are converted into concrete student activity. Finally, repeated movement into Course Information and Navigation suggests that design reasoning is intertwined with contextual constraints and platform affordances, which implies that chatbot support may be most effective when it helps teachers maintain conceptual coherence while also managing feasibility and tool-related actions.

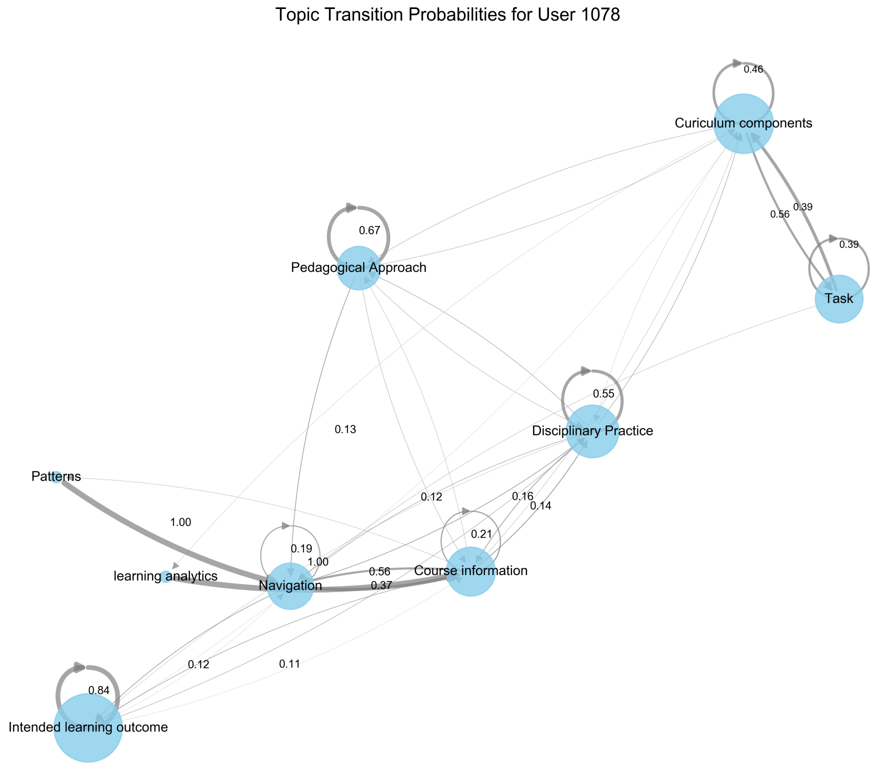

Figure 2: Theme transition of one student

3.2. How novice learning designers use the Chatbot in their design process

In this section, we explore how novice designers (students) in the course made use of the chatbot in their learning design process. Figure 3 shows how the thematic focus of each conversational turn evolved sequentially over time for the longest designer-chatbot dialog. As shown in the figure, there were many "greetings" from the chatbot. These indicate that the instances when the student resumed interaction with the chatbot after some time (varying from several minutes to days or weeks). We have segmented the figure into blocks. While there could be several "greetings" within each block, the time gaps are generally between several minutes to an hour, indicating that the student had been continuously working on the learning design task even though the interaction with the chatbot was not entirely continuous. On the other hand, there were significant time gaps of a day or up to several weeks between blocks.

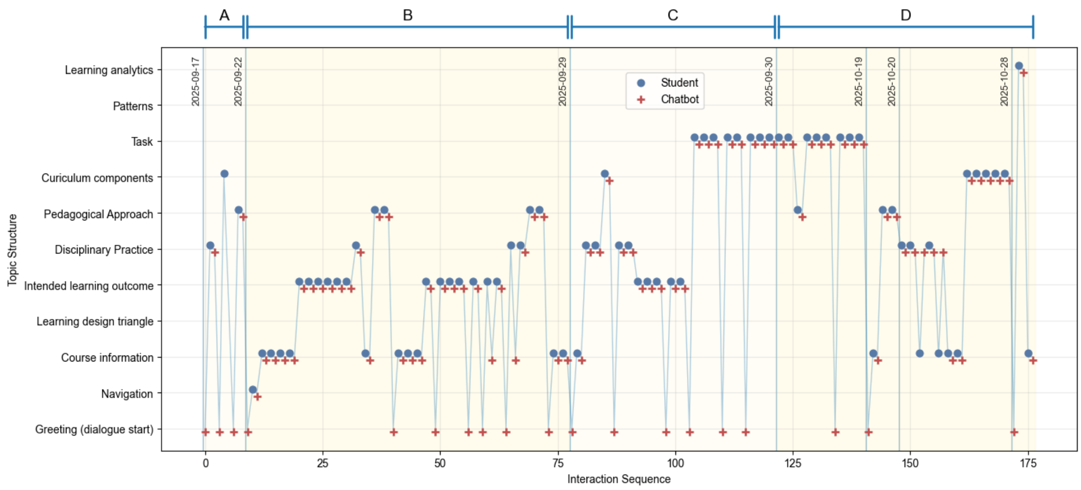

Figure 3: Evolution of novice designer-AI interaction themes over time for one student.

Block A (see the top of Figure 3) comprised interactions at the start of the course and there were only a few exchanges in which the student simply wanted to ask for the meaning of the three terms that were unfamiliar to him: disciplinary practice, curriculum components and pedagogical approach. This was followed by Block B, which comprised the most extended number of exchanges. It is important to note that each of the 7 breaks in the dialog indicated by "greetings" were mostly a few minutes apart, and the longest break was only about 50 minutes, and the entire block was about 7 hours 50 minutes in total. Most of the conversation circled around intended learning outcomes followed by course information, while the dialog also touched on disciplinary practice and pedagogical approach. Apparently, there was not too much design work carried out during these interactions. The student wanted to clarify the meanings and relationships among these core concepts.

Block C was another intensive period of interaction with the chatbot, but the foci and the time separation between each set of dialogic turns were longer, varying between 30 minutes to several hours. The student was working intensively on the design task during a full day. The dialog started with clarifying the more global design aspects—disciplinary practice, curriculum components, and intended learning outcomes. Then the dialog moved to persistent dialogs about task design. The time separation profile in the dialogic sequence indicates that the student was undertaking design work and consulting the chatbot along the way.

There was then a break of 20 days before the student consulted the chatbot again (Block D). During this period, the course required students to engage in intensive design activities. Block D was essentially an uninterrupted dialog during which the student asked questions about all of the key concepts except intended learning outcomes. The date of this dialog block coincides with the time when students need to complete their learning design before moving on to the design of learning analytics. It thus appears that the student was consulting the chatbot to check if they had misunderstood or missed something important about these concepts in their designs.

Overall, results presented in Figure 3 show that the chatbot served different functions for the student during different phases in the design process. Future work should examine the contents of the students' questions and concerns over the different phases.

4. CONCLUSION

This study introduces a framework-informed coding scheme to characterize novice designers' conversational themes when using a GenAI-based chatbot embedded in an online learning design tool during the design process. It models how these themes evolve over time through transition-pattern analysis. The results show that participants often sustained extended reasoning around intended learning outcomes and pedagogical approaches, and they repeatedly moved between curriculum components and task design, which reflects an iterative alignment process rather than one-off drafting. The transition networks also show that designers regularly shifted into course-context and navigation-related talk, suggesting that design reasoning is intertwined with clarifying constraints and managing platform actions. Together, these findings provide evidence about where novice designers tend to need the most support, and they point to concrete opportunities for GenAI-supported learning design environments to scaffold outcome formulation, strengthen alignment between curricular elements and tasks, and reduce friction when designers reconcile ideas with context and feasibility.

The plot of the sequential evolution of novice designer-AI interaction themes for the student with the longest dialog show that after an initial familiarization, the student's interaction with the chatbot occurred over three intensive periods, each with a different focus. During the first period, the student's interactions focused on gaining in-depth understanding of some core overarching concepts related to learning design, with specific focus on intended learning outcomes, course information and pedagogical approach. Engagement in actual design work on the learning design platform was light, as reflected by the short time gaps between each spurt of back-and-forth dialog. During the second period, the student's interactions with the chatbot was interlaced with longer periods of 30 minutes to several hours of design work. During this time the dialog moved from the overarching concepts to a focus on task design, indicating that the student was heavily engaged in actual design work, and only consulted the chatbot for some specific issues. The third intensive period of consultation occurred three weeks later, with a sequence of uninterrupted dialogue, covering a wide range of topics. The timing of this period coincided with the time point when students had to present their full learning design before moving on to the development of learning analytics questions and visualizations. This preliminary study is limited by the small number of participants and by focusing on first-level themes in a sampled subset of the dialogue data. Future work will increase the sample size, compare interaction patterns across different learning design projects and groups, and extend the analysis to second-level codes to capture finer-grained design reasoning and help-seeking moves. A further step is to relate distinct transition trajectories to the quality of the resulting learning designs and to indicators of agency and accountability during human–AI co-design.

References

[1] Z. Chen, T. Zhang, M. Taub, How does a data-informed deliberate change in learning design impact students' self-regulated learning tactics?, Journal of Learning Analytics 11 (2024) 174–196.

[2] P. Goodyear, Teaching as design, Herdsa review of higher education 2 (2015) 27–50.

[3] J. Dalziel, G. Conole, S. Wills, S. Walker, S. Bennett, E. Dobozy, L. Cameron, E. Badilescu-Buga, M. Bower, The larnaca declaration on learning design—2013, in: Learning Design, Routledge, 2015, pp. 1–41.

[4] Centre for Information Technology in Education, The University of Hong Kong, About us – learning design studio™, https://lds-info.cite.hku.hk/about-us/, n.d.

[5] N. Law, L. Liang, A multilevel framework and method for learning analytics integrated learning design, Journal of Learning Analytics 7 (2020) 98–117.

[6] I. Celik, S. Kontkanen, J. Laru, A. A. Dalyanci, Co-constructing adaptive lesson plans with genai:

Pre-service teachers' intelligent-tpack and prompt engineering strategies, Computers & Education (2025) 105485.
[7] B. Divjak, B. Svetec, P. Vondra, J. Badari, D. Grabar, Learning design with an ai assistant, in: International Conference on Artificial Intelligence in Education, 2025, pp. 207–220.
[8] R. C. Kerr, H. Kim, From prompts to plans: A case study of pre-service efl teachers' use of generative ai for lesson planning, English Teaching 80 (2025) 95–118.
[9] M. Moundridou, N. Matzakos, S. Doukakis, Generative ai tools as educators' assistants: Designing and implementing inquiry-based lesson plans, Computers and Education: Artificial Intelligence 7 (2024) 100277.
[10] S. Rojas-Drummond, O. Torreblanca, H. Pedraza, M. Velez, K. Guzman, 'dialogic scaffolding': Enhancing learning and understanding in collaborative contexts, Learning, Culture and Social Interaction 2 (2013) 11–21.
[11] M. Vollstedt, S. Rezat, An introduction to grounded theory with a special focus on axial coding and the coding paradigm, in: G. Kaiser, N. Presmeg (Eds.), Compendium for Early Career Researchers in Mathematics Education, ICME-13 Monographs, Springer, Cham, 2019, pp. 81–100. doi:10.1007/978-3-030-15636-7_4.

5. Acknowledgments

The authors acknowledge funding support for this study from the Research Grants Council of the HKSAR (GRF Grant #17610423) and the University Research Committee (URC Grant #2401102970) at the University of Hong Kong.

Declaration on Generative AI

The authors have used ChatGPT to help revise the manuscript for grammar and fluency improvements, ensuring that the text is clear and natural.