

Support–Guide–Release: Construction and Practice of a Three-Stage Progressive AI-Empowered Teaching Model for Research Methods Courses

Lu Xiang

Zhaoqing University, Zhaoqing, Guangdong, China

Abstract: With the fast growth of generative artificial intelligence (GenAI) come new challenges and opportunities for higher education. To address the tension between the powerful content-generation ability of GenAI and the cultivation of students' independent research ability, and supported by the zone of proximal development theory, cognitive load theory, and human–machine collaboration theory, this study constructs an AI-empowered, three-stage progressive teaching model (the "Support–Guide–Release" model), and completes a full round of teaching practice with 173 students enrolled in two research methods courses. The paper systematically explains the logic of AI's role at the three stages: initial topic exploration, literature review optimization, and research design, and presents three core design principles: limited assistance, authentic data bottom line, and progressive empowerment. For each stage, concrete examples of instructional prompts are also given. Based on the feedback from practice, the combination of stage-by-stage scaffolding is able to effectively alleviate the learners' initial cognitive load; the "independent work first, then AI" process design can effectively enhance the self-correction ability of students; the authentic-data bottom line can effectively enhance students' identification with research norms. In response to the problems that have been revealed when putting this into practice—namely, cognitive-load overload, the lack of criteria for evaluating AI use, and superficial disclosure—this paper proposes improvement strategies and an evaluation scale, and hopes to provide an actionable practical example for the teaching reform of research methods courses.

Keywords: Generative Artificial Intelligence; Research Methods Courses; Human–Machine Collaborative Teaching; Scaffolding Theory;

Teaching Model

1. Problem Statement

Generative AI, exemplified by ChatGPT, has made a swift impact in the education sector after the end of 2022 and has launched a wide range of debates regarding the transformation of higher education models. Previous studies reveal that the performance of generative AI varies significantly from one discipline to another, and it can be used to assist teachers and to act as a virtual tutor for students, yet it also has issues like creating inaccurate information and creating risks to academic integrity [1-3]. Also, the Ministry of Education and two other departments released the *Several Opinions on Promoting Interdisciplinary Integration and Accelerating the Cultivation of Graduate Students in the Field of Artificial Intelligence in "Double First-Class" Construction Universities* (Jiao Yan [2020] No. 4) in 2020, explicitly requiring the enhancement of the training of AI talents in universities and the inclusion of AI literacy in the system of disciplinary and professional training. At the same time, systematic literature reviews also reveal that the ecology of higher education is being vastly changed in various aspects by the implementation of generative AI, such as in supporting teaching and learning, assessing learning, and managing academic integrity [4]. Research methods courses aim, as their core objective, to cultivate students' logical thinking, empirical norms and problem-solving ability, and have such complex disciplinary characteristics as logical rigor, data authenticity and metacognitive monitoring. The number of studies on the use of AI in education has been growing in recent years. According to Kasneci et al., AI plays an auxiliary role in literature search, paper structure optimization, and language polishing; excessive reliance on AI, however, may result in the "hollowing out" of students' research ability [5]. Dillenbourg conducted a systematic review of the development trends of AI in the field of education

and pointed out that, in the development of learning technology, the subjectivity of teachers and students has become more prominent and AI should serve as scaffolding to support learning rather than as a replacement [6]. In the context of learning paradigm transformation, Zhu Zhiting, Dai Ling et al. introduced the concept of "high-consciousness generative learning" which calls for learners to have consciousness and critical thinking in AI-assisted learning [7]. Yu Shengquan and Wang Fancong revealed the risk of "cognitive outsourcing" in AI educational applications, and proposed practical paths to prevent it through human-machine collaboration strategies [8]. Zhu Yongxin and Yang Fan explored, in a macro perspective, the opportunities and challenges that generative AI poses to the innovation of education [9]. At an even bigger scale, Molenaar proposed the idea of hybrid human-machine intelligent learning technologies [10] and Cukurova described a hybrid-intelligence learning environment where learning, learning analytics and artificial intelligence are tightly coupled together [11]. A review of the current research, however, shows that existing research primarily concentrates on the application potential of AI as a general-purpose tool, or only on the macro level of principles and governance frameworks for human-machine collaboration. However, what is missing is a functional teaching model that integrates AI tools into students' learning through a staged and strategic approach in specific contexts within various courses and provides an explicit pathway for AI withdrawal. There is a fundamental conflict here that needs to be addressed more fully: how to use the powerful content creation capabilities of generative AI while fostering students' independence in research. As AI becomes easier to use, students' drive and methodical preparation to independently perform research tasks will be undermined; and a strict prohibition on AI use will result in a loss of its added value for learning. For courses in research methods, this tension is exacerbated because these courses lack operational rules and practices for adaptively changing the level of AI engagement according to the level of students' ability development, and there is a lack of process-oriented reflection and improvement based on real teaching practice.

Based on the above core tension, the following questions are raised in this study: How can a progressive AI-empowered teaching model be

built for research methods courses? What is the effectiveness of this model in actual teaching? What problems are encountered when implementing this model, and how can these be addressed? Based on this, this study aims to construct and implement the three-stage progressive AI-empowered teaching model (hereinafter referred to as "Support-Guide-Release" for short), systematically explain the instructional design of each stage and the role of AI in each stage, and present the implementation by combining classroom observation with student feedback, so as to give a practical scheme for the teaching reform of research methods courses.

2. Theoretical Basis and Design Principles

The instructional design of this study is based on three core theories: the zone of proximal development theory, the cognitive load theory, and the human-machine collaboration theory. The structural logic, content organization and boundary of AI involvement in the model are respectively determined by these three theories (see Table 1).

Vygotsky's theory of the zone of proximal development (ZPD) suggests that cognitive functioning can be moved to a higher level with the support of a more competent other, and that the level of support should be decreased as the learner's competence increases. In addition, empirical research based on this theory also shows that technology-enhanced feedback and scaffolding can be effective in fostering the establishment of learners' deep understanding [12] and Polly and Byker also showed the value of this theory in supporting technology-enhanced instructional design [13]. In this model, AI serves as the "more capable partner" to offer students scaffolding as needed within their ZPD. The essence of the three stages is that the proportion of AI participation gets gradually smaller as the course progresses, and the proportion of student autonomy gets gradually larger, which creates a teaching rhythm of "supporting the students first, and releasing them later". The core idea of this model is, therefore, summarized as "Support-Guide-Release": AI scaffolding with different functions and different levels of participation in the scaffolding is configured at different stages of students' ability development in research, and the scaffolding is removed step by step.

The staged instructional design is directly based on the cognitive load theory that was introduced by Sweller [14]. According to this theory, the

capacity of human working memory is limited and instructional design should aim to reduce extraneous cognitive load, optimize intrinsic cognitive load, and direct limited cognitive resources towards deep learning. The control of extraneous load is especially important in digital learning environments with the support of AI tools [15]. When students are asked to learn about research methods, AI utilization, and research design thinking at the same time, their cognitive load will easily exceed the capacity of working memory in the AI-empowered teaching. Therefore, this research adopts the staged load reduction method: In the first stage, AI can do more of the divergent idea-generation work to reduce the difficulty of the task; the second stage focuses on training students' critical judgment in literature review; in the third stage, students are required to operate fully independently, and AI assists only with technical operations.

The human-machine collaboration theory can be used to establish the boundary of AI intervention. It is a theory that proposes that in collaborative

human-machine interaction, clearly defining the roles of human and artificial intelligence, with humans always taking the lead, is essential for effective interaction. In an educational environment, this translates to using AI as a cognitive companion rather than an answer provider, and to students thinking and making decisions independently with the help of AI. Therefore, this study establishes the principle of limited assistance, that is, AI can inspire students, give them clues from the literature, give them structural suggestions, but cannot replace students in completing core research tasks. This is present in all three stages, where AI is always in a secondary role. Based on this, the model further has a clear functional boundary and exit mechanism of artificial intelligence participation, that is, when students' ability gradually increases, the AI participation level gradually decreases to the level of technical assistance in the third stage. The design red line is thus "limited assistance" running through the model.

Table 1. Theoretical Foundation and Instructional Translation Logic of the Three-Stage Model

Theoretical Basis	Core Proposition	Logic of Instructional Translation	Function in the Three-Stage Model
Zone of proximal development theory	Learners can reach higher cognitive levels with assistance; scaffolding should be removed as ability improves	Establish a progressive removal strategy: AI involvement decreases as the course advances, while student autonomy increases	Structural logic of the model: AI involvement high → medium → low; student autonomy low → medium → high, realizing the cognitive progression of "Support-Guide-Release"
Cognitive load theory	Instructional design should reduce extraneous load, optimize intrinsic load, and focus cognitive resources on deep learning	Implement a staged load-reduction strategy: lower the threshold of AI operation and free working memory for higher-order thinking	Core function of the third stage: AI supports only at the level of technical operation and comprehension assistance, while students independently complete research design decisions
Human-machine collaboration theory	AI should serve as a cognitive partner to assist decision-making, rather than replace human judgment	Establish the principle of limited assistance: AI provides inspiration and structural suggestions, while core research decisions are completed independently by students	Runs through all stages: AI's role shifts from a spark of ideas, to a mirror for dialogue, to an auxiliary tool, always remaining in a subordinate position

3. Three-Stage Progressive Instructional Design

Based on the above theoretical foundations, three core design principles are established. First, the principle of limited assistance: AI tools can be used only in specific components and to a limited degree. While AI can offer inspiration, clues for literature, and structural suggestions, it cannot replace students in fulfilling the core research task. Second, the authentic-data bottom line principle.

To ensure the rigor of research methodology training and academic integrity, all the empirical research components must have real data; it is not allowed to use AI to create fake data. Third, the principle of progressive empowerment. The introduction of AI tools is not one-off but is gradually adjusted as the course progresses: divergent inspirations in the first stage, convergent optimization in the second stage, independent assistance in the third stage. This means that AI shifts gradually from "dominant

assistant" to "staying behind the scenes" and that students' autonomy is slowly increased in step-

by-step fashion (see Figure 1).

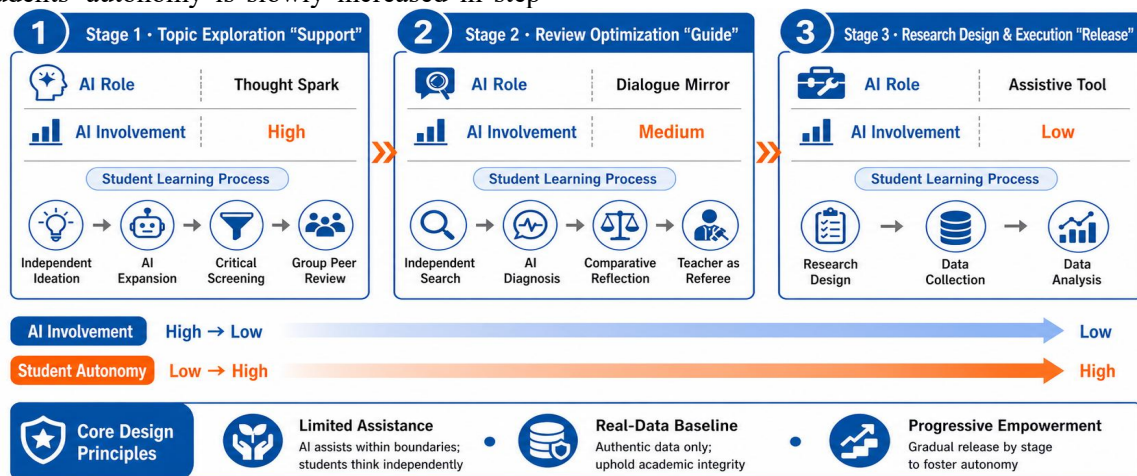


Figure 1. The Three-Stage Progressive AI-Empowered Instructional Design Model

3.1 Stage One: Initial Topic Exploration—"Support"

Stage One aims to help students broaden their research horizons and move from vague interests to specific researchable questions. AI is positioned as a "spark of ideas", mainly for divergent thinking and to inspire the choice of topic and broaden research horizons. The amount of AI involvement is highest here, but it is limited to the level of divergent thinking and does not involve forming research conclusions. The teaching process comprises four steps: independent ideation (drawing a personal interest map), AI expansion (multi-perspective brainstorming), critical screening (evaluating arguments), and intra-group peer review (peer and teacher feedback). The key lies in the process design: "work independently first, then use AI, then critique". At this stage, the following example of an effective prompt is provided to help students use AI properly:

"During my practicum, I noticed that students rarely ask questions proactively in mathematics class, and I am very interested in the topic of 'classroom questioning behavior'. Based on this observation, please propose two or three feasible research questions from different perspectives, such as motivation theory, classroom interaction theory, and learning community theory, and explain the research subjects and general methods for each question."

The focus of assessment at this stage is whether students can make informed choices among the multiple perspectives offered by AI, rather than merely listing or wholesale accepting them.

3.2 Stage Two: Literature Review Optimization—"Guide"

Stage Two aims to help students complete a literature review, establish the theoretical framework of the research, and form a clear logical chain. The AI at this stage is a "mirror for dialogue" and is mainly used to sort out the literature, identify logical gaps, and refine expressions. Students, however, must act as "judges" to evaluate the reasonableness of AI's suggestions. The teaching process includes four steps: independent search, AI diagnosis, comparative reflection (completing an AI Feedback Processing Form), and teachers' final judgment. The core mechanism is the "AI Feedback Processing Record Form", designed to promote students' in-depth metacognitive reflection. The following is an example of an effective prompt at this stage:

"The following is a literature review I have written on 'the impact of the flipped classroom on students' deep learning' (original text attached). Please provide feedback from the following three aspects: First, is the literature coverage comprehensive? Are there any important studies from the past five years missing? Second, does my argumentation contain any logical leaps or inversions of cause and effect? Third, are the transitions between paragraphs smooth? Please note that I only need you to point out the problems and suggest directions for revision; I do not need you to rewrite it for me."

At this stage, the assessment focus is on the students' ability to recognize valid information and the limitations in AI feedback, and independently make judgments on the literature under the guidance of teachers.

3.3 Stage Three: Research Design and Implementation—"Release"

The objective of Stage Three is for students to be able to independently complete research design, data collection, and data analysis, and form a complete research outcome. AI is more of an "auxiliary tool", so that at this stage it can only assist with technical operations and is not involved in the research design or data interpretation. In this phase, AI involvement is the lowest and student autonomy is the highest, and the authentic-data bottom line is the core principle. The following is an example of an effective prompt that can be used in the empirical stage:

"I conducted an independent samples t-test on 120 questionnaires using SPSS, and the results were $t = 2.37$, $p = 0.019$, Cohen's $d = 0.43$. Please help me interpret what these statistical results mean, especially what the effect size indicates. Please note that I only need an interpretation of the statistical results; I do not need you to write the discussion section for me."

The focus of the assessment at this stage is the reasonableness of the research design, standardization of data collection, and consistency of conclusions and evidence.

4. Teaching Implementation, Feedback, and Reflection

4.1 Implementation Overview and Analysis of Effectiveness

This model completed a full round of practice in two research methods courses, enrolling 140 students majoring in primary education and 33 students majoring in educational technology, totaling 173 students. The course was a one-semester course and each stage took about 4–5 weeks. Classroom observation records, student reflection reports (one per student for each phase) and staged assignments and final research papers were used as data sources. Three areas of

effectiveness are identified from the classroom observations and reflection reports.

The stage-by-stage scaffolding proved to be effective in reducing students' perceived cognitive load in the initial stages of using AI. In Stage One, over 78% of the students reported in their reflection reports that the brainstorming feature of AI "eased the psychological pressure of topic selection" and "made vague interests concrete". Restricting AI's function to divergent thinking avoided requiring students to master all research design elements at the very beginning. This is consistent with the predictions of cognitive load theory: AI took over some of the cognitive load, freeing working memory capacity for more valuable thinking activities.

Second, "work independently first, then use AI" greatly enhanced students' self-correction mechanism. Statistics show that more than 85% of the students made two or more rounds of self-revision at the topic selection stage (that is, they adjusted their initial direction before AI was involved), and more than 60% of the students made "partial rejection" judgments about AI feedback at the literature review stage. This shows that students did not passively accept AI output, but maintained a critical stance both before and after AI involvement, reflecting the true dialogic nature of human-machine collaboration.

Third, the authentic-data bottom line deepened students' identification with research norms. Over 90% of the students mentioned in their final reflections that "the data I collected myself gave me a greater sense of achievement" and "only when using real data did I feel I was doing research". It has a positive pedagogical function rather than being merely a prohibition—strengthening students' engagement with and identification with the empirical research process, thereby returning research training to its essence.

4.2 Implementation Challenges and Iterative Improvement Strategies

Table 2. AI Usage Level Evaluation Scale

Level	Name	Score	Cognitive engagement	Typical behavioral description
L1	No use	1	No AI involvement	No AI tools were used throughout the entire assignment/research process; the student relied wholly on independent individual effort to complete all components, including topic selection, literature searching, writing, and revision.
L2	Simple query	2	Passive reception	AI was used only as an information retrieval tool for lower-order content such as term definitions, formatting

				conventions, and factual information; AI output was not incorporated into deeper thinking or content generation.
L3	Assisted understanding	3	Shallow processing	AI was asked to explain the meaning of statistical results, sort out viewpoints in the literature, or break down complex concepts for the purpose of facilitating personal understanding; AI was not asked to directly generate research content or participate in the writing.
L4	Collaborative generation	4	Active construction	The student worked collaboratively with AI to refine research questions, optimize the paper structure, polish language, and generate a framework for the first draft. The student selected, integrated, and re-created based on AI output, with AI substantively participating in content production.
L5	Critical dialogue	5	Metacognitive reflection	The student evaluated the reasonableness and limitations of AI feedback item by item, explicitly recorded the reasons for accepting or rejecting it, and engaged in multiple rounds of argumentative dialogue with AI. This ultimately produced an in-depth metacognitive reflection record and achieved an integration of AI output at a higher level.

Three prominent problems emerged in practice, and corresponding improvement strategies were developed.

Regarding the challenge that cognitive load was "transferred rather than eliminated", some students said in their reflections that although the first stage had lowered the threshold of topic selection, "when faced with a dozen or more research directions generated by AI, I felt even more anxious instead"—their cognitive load had shifted from "being unable to think of a topic" to "finding it difficult to decide when faced with too many options". This reveals a subtle point in scaffolding design: the way and timing of scaffolding withdrawal are equally critical. Improvement strategy: The processing of AI feedback was subdivided into three micro-steps: "categorize and organize → judge item by item → compare and record" and students were asked to discuss the output of AI in small groups prior to making their own choices, thereby further reducing the cognitive load by distributing the decision-making pressure among peers.

Second, in the context of the problem of the lack of evaluation criteria for the use of AI, teachers and students at the initial stage of implementing AI lacked consensus on what level of AI use was acceptable and what constituted high-quality AI assistance, leading to subjective and inconsistent evaluation. Vague evaluation criteria not only affected the fairness of assessment but also made it difficult for students to form a clear sense of self-regulation. Improvement strategy: This study developed and implemented the *AI Usage Level Evaluation Scale* (see Table 2), which specifies

five levels—from L1 (no use at all) to L5 (critical dialogue)—with corresponding levels of cognitive engagement and typical behavioral descriptions, providing teachers and students with clear criteria.

Third, regarding insufficient depth of AI-use disclosure, some students' AI-use disclosure was merely perfunctory. They used vague statements such as "ChatGPT was used as an aid in this assignment". These phrases provided little information to help readers assess the extent of AI use or to help students reflect on their own use of AI. Improvement strategy: students were given a structured reflection template and were required to answer the following questions stage by stage: ① Which parts of this stage did you utilize AI in? ② What suggestions did AI make? ③ Which suggestions did you accept, modify or reject, and why? ④ How has your understanding of the research question changed because of your use of AI in this stage? A peer sharing mechanism has also been put in place, to replace "perfunctory disclosure" with "mutual learning".

5. Conclusion

The "Support-Guide-Release" three-stage progressive instructional model constructed in this study provides a feasible path out of the dilemma of "over-reliance" versus "total prohibition" in research methods courses in the AI era. The key contribution of the model is not the development of a completely new approach to using AI, but the systematic integration of the logic of scaffolding withdrawal into the process

of AI empowerment, allowing AI to gradually shift from "leading supporter" to "bystander" and finally yield to students' independent thinking. It is exactly this evolutionary logic that constitutes the concrete instructional translation of the zone of proximal development theory in the AI era.

From this round of practice, three transferable core principles can be further distilled. First, progression instead of prohibition. Instead of the two extremes "banning AI" and "laissez-faire use", different levels of AI involvement and exit points are set at different stages, enabling students to gradually develop independent research abilities while receiving necessary support. Second, authentic data as the bottom line. As AI-generated content becomes increasingly realistic, the authentic empirical process itself has become an "irreplaceable scarce resource" for training students' research ability—not only a strict requirement of academic norms, but also a fundamental guarantee of teaching effectiveness. Third, disclosure and reflection to foster metacognition. AI-use disclosure shifts from a "passive statement" to "active reflection". Structured records and evaluation promote students' monitoring of their own thinking processes, which is a key pathway for developing higher-order thinking. While these three principles are rooted in the teaching practice of the research methods courses, the essence of these principles (dynamic scaffolding, bottom-line adherence, and metacognitive promotion) is of some referential value for various higher-order thinking training courses in the AI era.

Future research can be conducted in the following directions: expand cross-disciplinary samples to test the universality of the model, explore the suitable matching points between the level of AI involvement and learner autonomy in different knowledge structure fields (e.g., humanities and social sciences vs. science and engineering), introduce longer-term longitudinal studies to test the long-term impact of this model on students' independent research competence, and further verify the applicability and validity of the AI Usage Level Evaluation Scale in different disciplinary contexts.

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