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Enhancing Learners' Question Competency in the Age of Generative AI: The DRIP Framework

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ABSTRACT

The rapid advancement of generative artificial intelligence (AI) is fundamentally reshaping educational paradigms. Tools such as ChatGPT, Claude, and Gemini now function not merely as information retrieval systems but as intelligent learning partners capable of supporting writing, problem-solving, coding, translation, and creative tasks through natural language interaction. Critically, the quality of AI-generated output is directly contingent on the quality of the user's prompt. This dependency implies that competitive learning ability in the AI era is determined less by the capacity to memorize information and more by the capacity to formulate, refine, and iteratively improve questions. This paper reconceptualizes 'question competency' as a core educational construct for the generative AI era and identifies six constituent elements: Problem Recognition, Context Design, Constraint Specification, Question Formulation, Critical Evaluation, and Iterative Prompting & Reflection. To operationalize this construct, we propose the DRIP (Data-Resonance-Insight-Problem) framework as a cyclic pedagogical model that begins with unstructured data encounter rather than pre-defined problem statements. The framework provides a replicable, AI-integrated instructional design applicable beyond statistics to any data-intensive discipline.

※ Keywords : Question competency, DRIP framework, prompt engineering, AI literacy

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1. Introduction

The rapid proliferation of generative artificial intelligence (AI) is transforming society and reshaping the educational landscape. Large language models (LLMs) such as ChatGPT, Claude, and Gemini have evolved beyond conventional information retrieval tools into interactive systems capable of natural language dialogue, personalized explanations, programming assistance, and creative content generation (Kasneci et al., 2023). Students increasingly incorporate these systems into coursework, self-directed learning, and assignment completion, while educators are beginning to use AI for instructional design and formative assessment.

Earlier digital technologies primarily enabled learners to search for, access, and select existing information. By contrast, generative AI can synthesize new content in response to user queries, provide explanations adapted to different levels of understanding, and facilitate dialogic interaction that supports and extends learners' thinking (Holmes et al., 2022). This development represents a shift in the educational role of technology from information retrieval toward collaborative cognitive engagement between learners and AI systems.

A defining characteristic of generative AI is that the usefulness and relevance of its output can be substantially influenced by the quality of the prompts provided by users (Liu et al., 2023; White et al., 2023). A vague query such as “Tell me about Antarctica” is likely to produce broad and generic information, whereas a precisely formulated and analytically structured question can elicit more focused responses. Effective learning with AI therefore depends not only on the ability to access or evaluate information but also on the ability to formulate, articulate, and iteratively refine meaningful questions.

This observation has important implications for education. Contemporary school instruction remains predominantly organized around a model in which teachers pose questions and students respond (Zawacki-Richter et al., 2019). Although this approach can support problem-solving within predefined constraints, it may provide limited structured opportunities for learners to identify problems independently and formulate their own questions (King, 1995; Chin & Osborne, 2008). If effective use of AI is understood not simply as technical proficiency but as the cognitive capacity to organize, develop, and refine one's thinking through questioning, educational practice should give greater attention to developing question competency. From this perspective, AI literacy should encompass not only the ability to use AI tools but also the ability to formulate

and refine questions that guide inquiry and learning.

This paper makes two principal contributions. First, it reconceptualizes "question competency" as a distinct and educationally significant construct for the generative AI era, complementary to existing conceptions of digital literacy and AI literacy. Second, it proposes the DRIP (Data-Resonance-Insight-Problem) framework as a cyclic pedagogical model for developing question competency and presents preliminary findings from a pilot implementation conducted in a university statistics capstone course. The remainder of the paper is organized as follows. Section 2 discusses paradigm shifts in learning associated with generative AI. Section 3 defines question competency and identifies its core elements. Section 4 presents the DRIP framework. Section 5 describes the pilot implementation and survey findings. Finally, Section 6 discusses implications and directions for future research.

2. Learning Paradigm Shifts and Question-Centered Learning in the AI Era

2.1 Generative AI and the Transformation of Educational Paradigms

The emergence of generative AI represents a significant shift from previous information technologies. Whereas earlier search systems primarily retrieved and presented existing information in response to user queries, generative AI can synthesize new text, images, and code from large-scale training corpora and generate explanations adapted to a learner's apparent level of understanding (Bubeck et al., 2023). This capacity for adaptive, generative interaction may further support the ongoing transition toward learner-centered education.

Rather than simply receiving information, learners can interact with AI systems as cognitive partners in the learning process (Holmes et al., 2022), defining problems, formulating questions, and critically evaluating AI-generated responses. Because generative AI can process natural language and produce contextually coherent responses, learners can engage in iterative dialogue that may progressively deepen their understanding. This creates a learning environment that differs from instruction based primarily on the one-way transmission of knowledge. In this context, effective use of AI involves more than knowing how to use a technological tool; it also requires learners to organize their thinking through effective questioning. This shift suggests the need to complement knowledge transmission with explicit opportunities for question-centered

inquiry.

This transformation is particularly relevant to the development of higher-order thinking skills. Traditional instruction can position students primarily as recipients of expert knowledge, whereas AI-integrated learning environments can provide greater opportunities for students to formulate questions that guide inquiry. The ability to identify what is not yet known, frame it as a researchable question, and critically evaluate the quality and relevance of AI-generated responses requires metacognitive awareness beyond memorization and routine problem-solving. Preparing students to engage effectively in such environments therefore represents an important challenge for contemporary education and underscores the need to develop competencies that enable learners to formulate, refine, and evaluate questions.

2.2 Prompts as Pedagogical Artefacts

A prompt can be defined as a natural-language instruction or query submitted by a user to a generative AI system. It is a primary means by which users communicate their intentions and guide AI-generated outputs (Liu et al., 2023; White et al., 2023). Prompt engineering has emerged as a recognized technical practice focused on optimizing input formulations to improve the quality and relevance of AI-generated outputs (Zamfirescu-Pereira et al., 2023). From a pedagogical perspective, however, prompts should not be understood solely as a technical artefact. It can also serve as an external representation of aspects of a learner's thinking. The purpose, context, constraints, and wording expressed in a prompt may provide indications of aspects of the learner's conceptual understanding, analytical intentions, and metacognitive awareness (Reynolds & McDonell, 2021).

Moreover, productive AI-assisted learning does not necessarily consist of a single exchange between a learner and an AI system. Learners may examine AI-generated responses, identify gaps or potential errors, and reformulate their questions through an ongoing cycle of inquiry and reflection. This iterative process resembles established models of reflective inquiry and highlights a form of learning activity that may not always be explicitly taught in formal education. Accordingly, educational practice should move beyond teaching learners to formulate technically effective prompts and foster the broader competency to design, evaluate, and refine questions through sustained intellectual engagement.

It is important to distinguish between generating a response and determining the

direction of inquiry. Although generative AI can respond to questions and suggest possible lines of inquiry, it cannot reliably determine what is meaningful, relevant, or worth investigating within a particular learning context. Decisions about the purpose, relevance, and direction of inquiry ultimately depend on human judgment. This asymmetry reinforces the importance of question competency, defined here as the capacity to identify problems, formulate meaningful questions, and iteratively refine them in response to emerging information and insights. In AI-assisted learning environments, question competency can therefore be understood as a central human capacity that enables learners to direct, evaluate, and derive value from interactions with generative AI.

3. Question Competency: Concept and Core Elements

Questioning has long been recognized in educational research as a fundamental mechanism of learning (King, 1995; Chin & Osborne, 2008). Questions are not merely means of obtaining information; they stimulate cognitive engagement and provide a starting point for knowledge construction. A learner who formulates a meaningful question has already engaged in substantial cognitive activity by identifying a gap in understanding, specifying what remains unknown, and framing that uncertainty as an investigable question.

Despite this recognition, prior research on AI-assisted learning has focused predominantly on prompt engineering as a technical skill, particularly on optimizing the formulation of inputs to improve the quality of AI-generated outputs (Liu et al., 2023; White et al., 2023; Zamfirescu-Pereira et al., 2023). This emphasis differs from conceptualizing questioning as a core learner competency. Prompt engineering primarily focuses on optimizing inputs to generate desired AI responses, whereas question competency focuses on the quality of the learner's cognitive process that gives rise to the question. A learner with well-developed question competency may receive an AI response that is technically imperfect while nevertheless developing substantial conceptual understanding through the inquiry process. Conversely, a learner with strong prompt engineering skills may produce high-quality AI outputs without necessarily engaging in the deeper reasoning required to interpret and apply those outputs meaningfully.

We define AI question competency as a set of cognitive and metacognitive abilities through which a learner working with generative AI can (i) recognize and frame a

problem, (ii) provide relevant context and specify appropriate constraints, (iii) formulate a clear and investigable question, (iv) critically evaluate AI-generated responses, and (v) iteratively reformulate questions and reflect on the inquiry process. This definition distinguishes AI question competency from prompt engineering by locating the primary focus on the learner's thinking and inquiry process rather than on the technical quality of AI-generated output. We further propose that AI question competency should be considered a distinct competency for the generative AI era, rather than simply a subskill of digital literacy or AI literacy. Its defining focus is the cognitive organization and development of inquiry, including the ability to determine what to investigate, how to formulate the inquiry, and how to revise it in response to emerging information.

We identify six constituent elements of AI question competency and their respective core functions as follows:

· Problem Recognition: Identifying a meaningful gap, phenomenon, or problem worthy of inquiry.

· Context Design: Providing relevant background and situational information for effective inquiry.

· Constraint Specification: Defining the scope, conditions, format, and boundaries of the inquiry.

· Question Formulation: Translating an observed phenomenon or problem into a clear and investigable question.

· Critical Evaluation: Assessing the validity, relevance, and limitations of AI-generated responses and analytical results.

· Iterative Prompting and Reflection: Revising questions based on emerging evidence and reflecting on the inquiry process.

These six elements should not be understood as discrete or strictly sequential skills. Rather, they are interdependent and operate through a cyclical process. Stronger Problem Recognition can lead to more purposeful Context Design and Constraint Specification; Critical Evaluation can reveal deficiencies that trigger Iterative Prompting; and Reflection can improve subsequent performance across the entire inquiry process. In this sense, AI question competency represents an integrated capacity for directing and developing inquiry through interaction with generative AI.

4. The DRIP Framework for Question Competency Development

We propose the DRIP framework as a cyclical pedagogical model for developing question competency in AI-integrated learning environments. DRIP reconceptualizes the starting point of inquiry. Rather than requiring learners to begin with a predefined problem, the framework begins with engagement with data and facilitates the emergence of questions through observation, interpretation, and interaction with AI. Data therefore serve not only as material for analysis but also as a stimulus for curiosity, insight generation, and problem formulation.

4.1 DRIP Framework

Existing statistics and data science curricula have been strongly influenced by the PPDAC (Problem-Plan-Data-Analysis-Conclusion) cycle proposed by Wild and Pfannkuch (1999) and subsequently incorporated into the GAISE College Report (Carver et al., 2016). PPDAC provides a coherent structure for statistical inquiry, particularly in contexts where the research problem is identified before data collection or analysis begins. However, in capstone and project-based settings, as well as in contexts involving heterogeneous datasets collected from web sources, learners may have difficulty formulating meaningful problems before exploring the available data. This challenge can be particularly pronounced among statistics and data science students with limited domain-specific knowledge of the substantive context represented by the data.

When a meaningful problem cannot be formulated at the outset, learners may devote disproportionate attention to applying statistical or computational techniques rather than developing an inquiry grounded in the characteristics of the data. The separation of problem formulation from data exploration can therefore hinder the development of an exploratory inquiry process. DRIP addresses this limitation by reorienting the initial direction of the conventional inquiry cycle: learners first encounter and explore data, identify points of resonance and generate insights through interaction with the data and AI, and subsequently formulate problems that can be investigated systematically. Thus, problem formulation becomes an outcome of inquiry rather than a prerequisite for it. Table 1 summarizes the structural differences between the PPDAC and DRIP frameworks.

〈Table 1〉 Structural Comparison of PPDAC and DRIP

Dimension	PPDAC	DRIP
Starting point	Problem	Data
Learning flow	Problem→Plan→Data→ Analysis→Conclusion	Data→Resonance→Insight→ Problem
Initial learner activity	Problem formulation and planning	Data exploration
Question emergence	Primarily after problem identification	Through Resonance and Insight
Role of AI	Not structurally specified	Integrated throughout the inquiry cycle
Problem formulation	Starting condition	Outcome of initial inquiry
Inquiry structure	Problem driven	Data stimulated and recursive
Primary pedagogical emphasis	Conducting systematic statistical inquiry	Developing question competency through inquiry

The four stages of the DRIP framework are defined as follows:

(1) Data: Learners are presented with raw or minimally structured data without a predefined analytical task or research problem. They explore the data by examining its structure, variable distributions, patterns of missing values, and categorical relationships. Generative AI can assist with interpreting the data schema, clarifying variable meanings, and conducting exploratory analysis, while decisions about which variables or features to examine remain with the learner. The absence of a prescribed problem is intentional, allowing questions to emerge through direct engagement with the data.

(2) Resonance: Learners identify patterns, anomalies, relationships, or other features that evoke curiosity, surprise, or a perceived contradiction. For example, in a book market dataset, learners may notice books with many reviews but relatively low sales rankings or publishers concentrated in particular genres. Resonance marks the transition from technical data exploration to recognizing phenomena that may warrant further inquiry.

(3) Insight: Learners use descriptive statistics, data visualization, and other appropriate analytical techniques to examine observed phenomena more rigorously. Generative AI can support code generation and interpretation of analytical outputs, but learners remain responsible for determining what the data support, considering alternative explanations, and identifying additional evidence that may be needed. This stage provides the analytical

basis for refining the emerging inquiry.

(4) Problem: Learners synthesize their observations and insights into a well-defined research problem, which is then articulated as a researchable question or set of questions that guides the next inquiry cycle. Examples include, “Are lower-priced books associated with a greater number of reviews?” and “Does the relationship between ratings and sales rank differ across book genres?” Because these questions emerge from learners' engagement with the data rather than being prescribed in advance, the DRIP framework establishes a recursive process in which each cycle generates new directions for inquiry.

The DRIP framework implies four principles for curricular redesign. First, statistical inquiry can begin with engagement with data rather than with a fully specified problem statement. Second, data exploration should be treated as a substantive learning activity rather than merely as a preliminary technical procedure. Third, question generation should be positioned as a central learning outcome alongside the application of statistical and computational techniques. Fourth, generative AI should be integrated as a source of cognitive support throughout the inquiry process, assisting with code generation, data schema interpretation, statistical exploration, and iterative dialogue while preserving the learner's responsibility for reasoning, evaluation, and judgment.

4.2 AI Question Competency and DRIP

Table 2 illustrates the correspondence between the six elements of AI question competency and the four stages of the DRIP framework. The six elements of AI question competency are not mapped to the four DRIP stages in a strictly one-to-one manner. Rather, each competency is activated with different levels of emphasis across the inquiry cycle. Problem Recognition and Question Formulation are particularly salient during Resonance and Problem, whereas Context Design, Constraint Specification, and Critical Evaluation become prominent during Insight. Iterative Prompting and Reflection operate across the entire cycle and enable the recursive transition from one DRIP cycle to the next.

〈Table 2〉 Mapping AI Question Competency Elements onto the DRIP Cycle

DRIP stage	Primary Question Competency Elements	Secondary Elements
Data	Problem Recognition	Context Design, Constraint Specification
Resonance	Context Design	Question Formulation, Reflection
Insight	Constraint Specification	Question Formulation, Critical Evaluation
Problem	Question Formulation, Critical Evaluation	Iterative Prompting and Reflection

5. Pilot Implementation and Survey Results

5.1 Implementation Setting and Dataset

As an initial pilot study, DRIP was implemented in a capstone design course for undergraduate statistics students at Jeonbuk National University (n = 18). The course was a final-year project course in which students conducted independent data analysis projects using real-world data. DRIP was adopted as the organizing framework for the course, in place of the conventional PPDAC-based structure that students had encountered in previous statistics courses.

The dataset was collected from YES24, a major online bookstore in South Korea, using an RSelenium-based web-scraping pipeline. Generative AI provided programming support throughout the data collection process, assisting with JavaScript DOM manipulation, designing response strategies to accommodate changes in site structure, optimizing crawling speed, and handling exceptions. The use of AI as a programming support tool, rather than simply as an answer-generation tool, was an intentional instructional design choice aimed at demonstrating human-AI collaboration in the programming process.

The final dataset comprised 154,523 book records across 26 top-level categories. Each record contained 16 variables, including title, author, publisher, publication date, reader rating, review count, sales index, bestseller rank, table of contents, and other bibliographic attributes. The raw HTML files totalled 56.37 GB, while the extracted CSV dataset was approximately 671 MB. The scale and heterogeneity of the dataset required students to make substantive data management decisions and provided a context for data-driven inquiry. Rather than relying on preprocessed instructional datasets, students engaged directly with the practical complexities of real-world data.

5.2 DRIP in Practice: Stage-by-Stage Description

(1) Data stage: Students were presented with raw HTML files and an extracted CSV file without a predefined analytical task. They explored data structure, variable distributions, patterns of missing values, and the hierarchical organization of book categories, with generative AI assisting in the interpretation of HTML structure and variable semantics. Students independently selected the variables and patterns they considered worthy of further examination.

(2) Resonance stage: Students identified patterns or anomalies that attracted their attention, including books with high review counts but relatively low sales indices, publishers concentrated in particular genres, and temporal clustering of publication dates. They documented these observations as initial analytical intuitions and articulated what surprised them, what they had not expected, and why a particular pattern warranted further investigation. This process supported question competency by encouraging students to distinguish potentially meaningful phenomena from superficial observations.

(3) Insight stage: Students used R to calculate descriptive statistics and produce data visualizations related to their observations. Generative AI supported code generation and interpretation of analytical outputs, while students remained responsible for interpreting and synthesizing the results, considering alternative explanations, and identifying limitations in the available evidence. This distinction between AI-supported computation and student-led interpretation was maintained throughout the course.

(4) Problem stage: Students formulated researchable problems and articulated them as original research questions based on insights from the preceding stages. Representative questions included: "Are lower-priced books associated with higher review counts?", "Does the relationship between reader ratings and bestseller rank differ by genre?", and "Do books with longer tables of contents receive higher average ratings?" These questions initiated subsequent DRIP cycles, returning students to the Data stage with more focused analytical directions. The recursive structure of DRIP was evident in the progression from initial observations to increasingly specific research questions.

Three recurring pedagogical patterns emerged during the course. First, learners shifted from a predominantly responsive role, in which they primarily addressed instructor-specified problems, toward a more active role in identifying and formulating problems. Within the DRIP framework, inquiry begins with engagement with data rather than with a prescribed research question, allowing problems to emerge through learners' exploratory interaction with the data.

Second, question generation was positioned as a primary learning objective alongside the application of statistical techniques. Student attention increasingly shifted from questions such as "How do I run this analysis?" toward "What question is worth asking?" and "What would the answer tell me?" This shift reoriented statistical inquiry from the application of analytical procedures toward the formulation of meaningful questions and the design of subsequent inquiry. Rather than emphasizing only the selection and

execution of analytical techniques, DRIP places greater emphasis on learners' ability to construct meaningful and researchable questions.

Third, interaction with generative AI supported the continuation and refinement of learners' inquiry processes. Through a Question–Answer Chain (QAC), initial inquiries could be progressively specified and elaborated through successive interactions with AI. QAC refers to an iterative sequence of questions posed by learners and responses generated by AI. When analytical progress stalled or the direction of inquiry became unclear, AI-mediated dialogue provided cognitive support by helping learners reconsider and reorganize their thinking, identify alternative analytical directions, and resume exploration. Generative AI thus functioned less as a provider of ready-made answers and more as an interactive resource for sustaining and extending learners' inquiry.

5.3 Post-Course Survey Findings

A post-course survey was administered to all 18 participants. Rather than measuring predefined outcomes using a standardized psychometric instrument, the survey invited students to describe, in their own words, their perceived changes in learning effectiveness, attitudes toward learning, active engagement, and question-generation ability. This open-ended design was adopted because the primary purpose of the pilot was to examine students' experiences with the DRIP approach rather than to test hypotheses concerning quantifiable outcomes.

This classroom activity was conducted as part of regular instruction and was not designed or conducted as a human subjects research study. Only the total number and proportion of students provided positive responses were calculated or recorded. Accordingly, the activity was considered outside the scope of human subjects research requiring IRB review.

Of the 18 students, 15 (83.3%) reported perceived development in active learning and question-generation ability. An exact two-sided binomial test against a 50% reference proportion indicated that the proportion of positive responses was statistically significant ($p = .008$). These perceptions were also evident in the Question–Answer Chains (QACs) produced during the course. Several students reported that they initially found it difficult to work without a predefined problem statement but gradually developed a greater sense of ownership over their inquiry. Some also noted increased awareness of the distinction between asking a question because it had been assigned and asking one because they genuinely wanted to understand the answer. Three students continued to experience

difficulty with the open-ended structure, suggesting a need for greater scaffolding during the initial stages of DRIP implementation.

The interpretive value of these responses is supported by the participants' prior experience with structured statistical inquiry. All 18 students had completed multiple statistics courses organized around the PPDAC framework, providing a basis for retrospective comparison between the two approaches. This experience enabled them to reflect on differences between conventional statistical inquiry that begins with a problem and the data-driven inquiry process introduced through DRIP.

These retrospective comparisons should nevertheless be interpreted with caution because they are subject to recall bias and do not provide a controlled baseline. Students' recollections of prior PPDAC-based instruction therefore serve as an informal reference point rather than a rigorously matched comparison condition. The survey findings are consequently treated as preliminary evidence of feasibility and learner receptivity rather than causal effectiveness. Controlled studies using validated measures and appropriate comparison groups will be necessary to evaluate the effects of DRIP more rigorously.

6. Conclusions

Generative AI systems can provide answers to users' questions, but they do not necessarily determine what questions are worth asking. The growing emphasis on prompt engineering therefore highlights the importance of formulating effective and meaningful questions. In the era of generative AI, questioning is not merely a communicative act but a central mechanism through which learners organize thought, direct inquiry, and construct knowledge. This paper reconceptualized AI question competency as a distinct educational construct comprising six interrelated elements: Problem Recognition, Context Design, Constraint Specification, Question Formulation, Critical Evaluation, and Iterative Prompting & Reflection. These elements extend beyond digital literacy, AI literacy, and prompt engineering by focusing on the cognitive processes underlying inquiry.

To operationalize this construct, we proposed the DRIP framework, a cyclical, AI-integrated pedagogical model that begins with engagement with data and allows questions to emerge through Resonance and Insight rather than requiring a fully specified problem at the outset. Compared with the established PPDAC cycle, DRIP is designed for project-based and capstone environments in which learners work with real-world

data and may have limited domain-specific knowledge. Generative AI serves as a source of cognitive support throughout the inquiry cycle while preserving learners' responsibility for interpretation, evaluation, and decision-making.

A pilot implementation at Jeonbuk National University provided preliminary evidence of the feasibility and learner receptivity of the DRIP approach. Fifteen of the 18 participating students (83.3%) reported perceived development in active learning and question-generation ability. These findings should be interpreted in light of the study's limitations, including the small sample size, absence of a control group, and reliance on retrospective self-report. The results therefore do not establish causal effectiveness but provide an initial basis for further investigation.

Future research should pursue four directions: (i) controlled comparisons of DRIP and PPDAC across matched student cohorts to examine differences in learning outcomes; (ii) development and psychometric validation of an AI question competency instrument capable of assessing performance across its constituent elements; (iii) development of rubrics for evaluating question quality, critical evaluation of AI responses, and iterative prompting across disciplines; and (iv) replication of DRIP beyond statistics, including in the social sciences, humanities, and professional education, to examine its generalizability as a design principle for AI-integrated curricula. At the curricular level, question competency warrants explicit consideration as a core competency for the generative AI era, while teacher education programs should prepare educators to design and facilitate question-centered, AI-integrated learning environments.

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