Inquiry-based learning patterns in large language model-driven learning environments: An exploratory study from Bloom's perspective

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Inquiry-based learning (IBL) is a problem-driven and exploration-centred learning method. The emergence of large language models (LLMs) such as ChatGPT provides a new interactive environment for IBL. However, research has not sufficiently explored how students interact with LLMs for IBL. This study aimed to understand students' behaviours interacting with LLM at different cognitive levels during the IBL process. We conducted an experiment on a data science academic writing task and used Bloom's educational taxonomy to examine the behavioural patterns of students' IBL at different cognitive stages. Through the exploratory thematic analysis of 117 interview transcripts, 370 interaction records and 1,694 minutes of screen recordings, we identified 14 interaction patterns among students at different levels of prior knowledge. This article discusses the potential impact of self-efficacy and metacognitive monitoring on students' learning behaviour in an LLM-driven learning environment and called for the design of a guiding planning framework and scaffolding to address challenges such as reliance on artificial intelligence. Our study provides new insights for the development of IBL in the era of emerging artificial intelligence technologies.

Implications for practice or policy:

- Educators can improve student inquiry-based learning outcomes by designing cognitive scaffolding that targets specific higher-order thinking stages.
- Instructional designers should develop planning frameworks that mitigate over-reliance on artificial intelligence while fostering student metacognitive monitoring.
- Policymakers could implement training programmes to enhance students' critical evaluation skills within an LLM-driven environment.

Keywords: inquiry-based learning, Bloom's taxonomy, large language model (LLM), thematic analysis, learning environment

Introduction

Inquiry-based learning (IBL) is a learner-centred learning approach that encourages students to ask in-depth questions, to explore independently, to reflect critically and to construct information and knowledge (Mamun, 2022; Pedaste et al., 2015). In an IBL environment, learners are not passively memorising knowledge but are prompted to identify meaningful questions, seek and evaluate information and build their own understanding through a cycle of continuous inquiry and reflection and revision (Bruder & Prescott, 2013; Khalaf & Mohammed Zin, 2018). IBL has been widely applied in the higher education field because of its ability to cultivate students' information literacy (Buchanan et al., 2016; Chen et al., 2017), critical thinking (Arifin et al., 2025; Duran & Dökme, 2016) and self-regulated learning (Bartel, 2015), which are essential skills for modern education.

As information overload continues to intensify, IBL is facing challenges in terms of efficiency (Lee et al., 2024). Recently, the emergence of artifical intelligence (AI), especially large language models (LLMs) such as ChatGPT, has had a profound impact on the educational paradigm (Lo, 2023; Luo & Wang, 2024; Montenegro-Rueda et al., 2023) and has also introduced new opportunities and development to support IBL. LLMs can serve as interactive cognitive partners, assisting students in tasks such as formulating research questions, retrieving relevant sources, analysing and summarising complex arguments (Bakas et al., 2023; Kumar et al., 2024). In LLM-driven learning environments, students are no longer confined to traditional information search methods but can engage in dynamic, conversational information seeking with the LLM, potentially accelerating and deepening the process of exploring and constructing knowledge (Luo et al., 2024).

However, despite growing interest in LLM-enhanced IBL processes, research has tended to focus on the teacher-led pedagogical practices and perspectives (Adeyele & Ramnarain, 2024; Moundridou et al., 2024; Ramnarain et al., 2025; Yeh, 2025) or the tools themselves (Ali et al., 2023; Fenske & Otts, 2024), and there is still limited understanding of how students use the LLM to engage in cognitive processes and information acquisition behaviours in IBL. In addition, few studies have theoretically explained students' learning process at different cognitive stages in this new interactive environment. Studying this interaction is crucial because it sheds light on how students move through the learning cycle of evaluating and integrating information with the support of the LLM to develop higher-order cognitive skills (Lee et al., 2024).

To address these gaps, this paper adopted a mixed research method, drawing on Bloom's taxonomy (Anderson & Krathwohl, 2001) to apply exploratory thematic analysis and frequency analysis to understand how students process information at different cognitive levels when interacting with an LLM in IBL. We conducted a data science-related academic writing experiment, which is a representative case in science, technology, engineering and mathematics in modern education and aimed to re-examine the dynamic interaction patterns between students and the LLM through a cognitive perspective, offering practical insights for educators and curriculum designers who seek to use LLMs to promote students' learning and information literacy.

Challenges for students using LLMs in IBL

LLMs provide great convenience for students' exploration in the IBL process, including knowledge discovery and personalised feedback (Wang et al., 2024). While LLMs can simplify the retrieval of relevant information, students may overestimate their accuracy, with LLMs reinforcing potential cognitive biases (Besharat-Mann, 2024) and leading to an undue sense of trust and dependency (Fuchs, 2023). Research by Kazemitabaar et al. (2023) showed that learners who combine their own coding strategies with AI suggestions perform better than those relying solely on AI-provided solutions. Stadler et al. (2024) indicated that although LLMs reduce mental work, they may harm the depth of students' scientific inquiry. Given that LLMs typically do not provide transparent source citations, students may struggle to verify the accuracy and reliability of the information provided. This is particularly concerning in academic settings, where plagiarism, incorrect citations and improper language use can lead to serious consequences (Dempere et al., 2023). Without the necessary review frameworks and analytical skills, students may become accustomed to accepting unverified information, forming a cognitive information cocoon (Sharma et al., 2024). Another concern is the inherent bias in the LLM output. Without proper guidance, these biases can be perpetuated or even amplified when students use LLMs uncritically (Barman et al., 2024).

Given the ongoing challenges, the effectiveness of LLMs in helping students explore and seek information has been questioned (Carroll & Borycz, 2024) but it is undeniable that LLMs are driving the transformation of learning systems, which is particularly significant in the process of student exploration and independent learning, especially when teacher guidance is limited. The ability to evaluate and synthesise information from multiple sources is a higher-order cognitive skill in Bloom's taxonomy (Krathwohl, 2002), and LLMs provide a learning environment that supports the development of this high-level cognition. While students face challenges in verifying accuracy and identifying bias in LLM-generated content, these same

challenges also present opportunities to foster critical thinking and autonomous learning (Shahzad et al., 2025). Understanding the limitations of LLMs and recognising how they may affect their own learning are important prerequisites for students to master LLMs (Razafinirina et al., 2024).

Bloom's taxonomy and its derivatives

Bloom's taxonomy is a widely recognised system for classifying educational objectives, regarded as a valuable measurement tool capable of defining the precise meanings of broad educational goals within a curriculum (Gates & Pugh, 2021). The cognitive domain was further subdivided hierarchically into the domains of knowledge, comprehension, application, analysis, synthesis and evaluation. The taxonomy is a cumulative, bottom-up hierarchy that forms a continuum from lower-order thinking skills to higher-order thinking skills. In particular, knowledge, comprehension and application are considered lower-order thinking skills, and the levels of analysis, synthesis and evaluation are considered to be the embodiment of higher-order thinking skills (Anderson & Krathwohl, 2001; Chandio et al., 2016).

However, the complexity of cognitive demands can vary depending on specific goals, which may make it difficult in practice to fully cover and address cognitive objectives using Bloom's taxonomy. Therefore, many scholars have made adaptive changes to Bloom's taxonomy to better meet the cognitive needs and goals required in different eras. Krathwohl (2002), one of the original contributors to Bloom's taxonomy, proposed a revised Bloom's taxonomy (RBT) shown in Figure 1. The revisions aimed to improve three key aspects: terminology, structure and emphasis (Forehand, 2010). Krathwohl replaced the noun-based categories of the original taxonomy with verbs, transforming knowledge into remembering, comprehension into understanding and synthesis into creating. Building on these revisions, Darwazeh (2017) proposed further refinements, such as repositioning metacognition as the most complex cognitive level and subdividing the remembering and creating levels into more detailed subcategories.

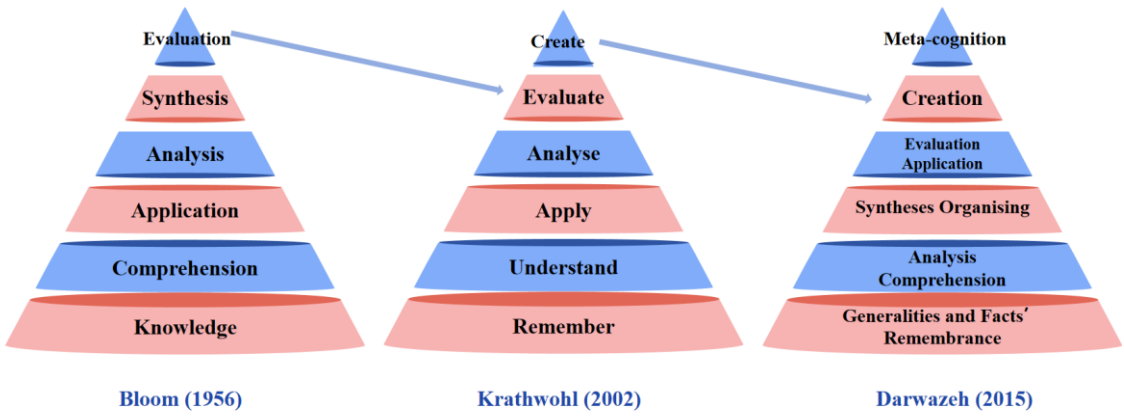

Figure 1. Development of Bloom's taxonomy

Given the evolving landscape of digital learning resources and the opportunities facilitated by educational informatisation, Churches (2008) first introduced Bloom's digital taxonomy (BDT), which is derived from Bloom's taxonomy, to reflect the integration of digital tools in education and guide the learning process under informatisation. As shown in Table 1, BDT still retains the pyramid structure of RBT but adapts the content of each level to information technology. Additionally, both 9 and social media tools have made innovations within the framework of RBT. Demir (2024) proposed a taxonomy of social media for learning, which redefined the levels of RBT into three major dimensions – awareness, cognition and creation – along with five sub-goals. It focuses on evaluating social media as a tool for students and teaching. Faraon et al. (2023) introduced Bloom's taxonomy based on AI by defining all levels of AI application and gave some examples of the practical application of basic LLM tools. Churches' BDT and derived theories are presented in detail in Table 1.

Table 1
Churches' (2008) BDT and its derived theories

BDT	Taxonomy of social media for learning		Bloom's taxonomy based on AI (Faraon et al., 2023)	
Level	Description	Example	Description	Example for ChatGPT
Phase 1: Remembering	Students view course content on private social media sites	Student teachers viewed course-related resources on group pages	Helps students search for basic knowledge	ChatGPT can generate a simple document containing basic concepts
Phase 2: Understanding	Lecturers post knowledge through online content	Student teachers presented their lesson preparation materials within a standard framework	Help students with reading comprehension	ChatGPT can generate a concise summary based on the paper uploaded by the student
Phase 3: Applying	Students interact with others on the network by sharing their ideas and insights	Student teachers developed a draft of teaching materials, discussing with their classmates in their groups	Helps students improve their writing performance	ChatGPT can output the text in an academic style
Phase 4: Analysing	Students collect valuable ideas from others and analyse them to put them into practice	Student teachers analysed the ideas and comments collected from their peers and applied them to their own work	Handles code errors in web development	ChatGPT can support learners when they encounter coding errors
Phase 5: Evaluating	Students evaluate the strengths and weaknesses of their work through self-evaluation and peer evaluation	Student teachers uploaded the teaching material and showed it to the group for feedback	Helps students use critical thinking when writing scientific reports	ChatGPT can check the logic and coherence of the argument and give overall improvement suggestions
Phase 6: Creating	Students curate work based on processes and experiences built from previous levels	Student teachers revised their materials based on feedback and presented again to the group	Generates ideas through divergent thinking for students	ChatGPT can brainstorm to generate multiple different viewpoints
Higher dimensions	Metacognitive process			

However, Faraon et al.'s (2023) Bloom's taxonomy based on AI mainly emphasises the purpose classification of AI tools, rather than focusing on the interaction process between students and these tools, which means that when using LLMs, students' guidance needs and their thinking process in information exploration and cognitive construction are simplified or even ignored. It may lead to hiding students' problems in the interactive learning environment of LLM, such as relying on tools instead of developing autonomous problem-solving when facing complex situations (Stojanov et al., 2024).

Methodology

The main purpose of this study was to investigate the experiences and interactions of higher education students in an interactive learning environment facilitated by LLMs during IBL. The goal was not to analyse the effects of cognition and variables but to gain a deeper understanding of how different types of students collaborate with LLMs by exploring their experiences and behaviours in the learning cycle.

This study used an exploratory thematic analysis, using Bloom's taxonomy as a preset structure to classify and summarise students' IBL practices. We established an IBL experiment based on the LLM environment and observed the performance of students at different Bloom cognitive stages in completing IBL tasks in an LLM-supported environment. The study selected the interpretation of cognitive stages based on Bloom's taxonomy of computer science and information science, developed by Habiballa et al. (2025, p. 8), as shown in Figure 2.

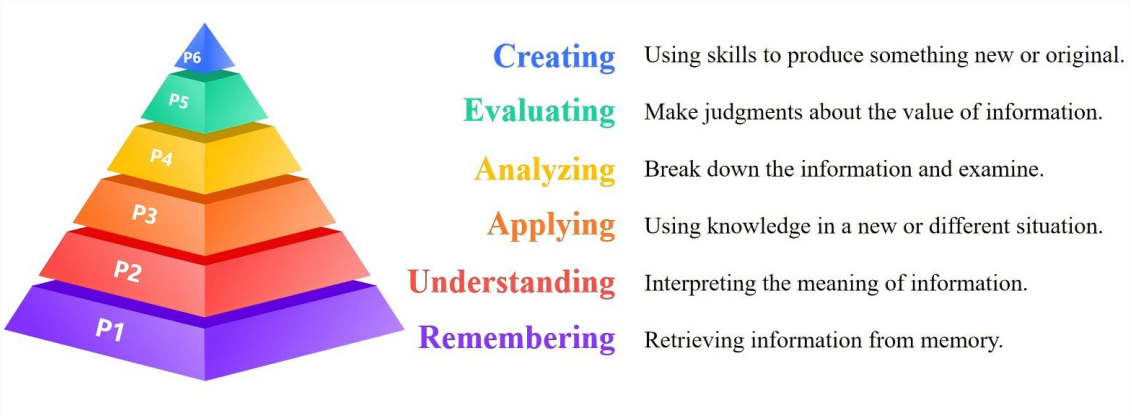

Figure 2. Cognitive stages in Bloom's taxonomy and corresponding information-related explanations

Task design

We assigned an IBL task to university students in of science, technology, engineering and mathematics. Specifically, participants were grouped into a discussion room-based environment and provided with an educational data set containing variables such as student characteristics and academic performance. Participants were asked to explore the data set, choose a research question they were interested in, uncover insights from the data and write an academic paper based on their findings. They were asked to use a designated LLM to help organise materials, express their ideas and request data analysis.

Figure 3 shows an example of participants using the LLM to assist in the IBL process, and Figure 4 shows a photo of participants taking part in an IBL experiment. They were also allowed to use other tools such as search engines or Python code, as long as those tools did not guide or influence their research direction. We did not provide strict guidance during the assignment. Only minimal guidance was provided in the lectures at the beginning of the assignment to ensure the effectiveness of IBL (Bruder & Prescott, 2013; Sam, 2024). However, considering that guidance has a significant impact on IBL outcomes, we allowed participants to seek help from teachers when needed. However, teachers were instructed not to directly influence or guide students' research results.

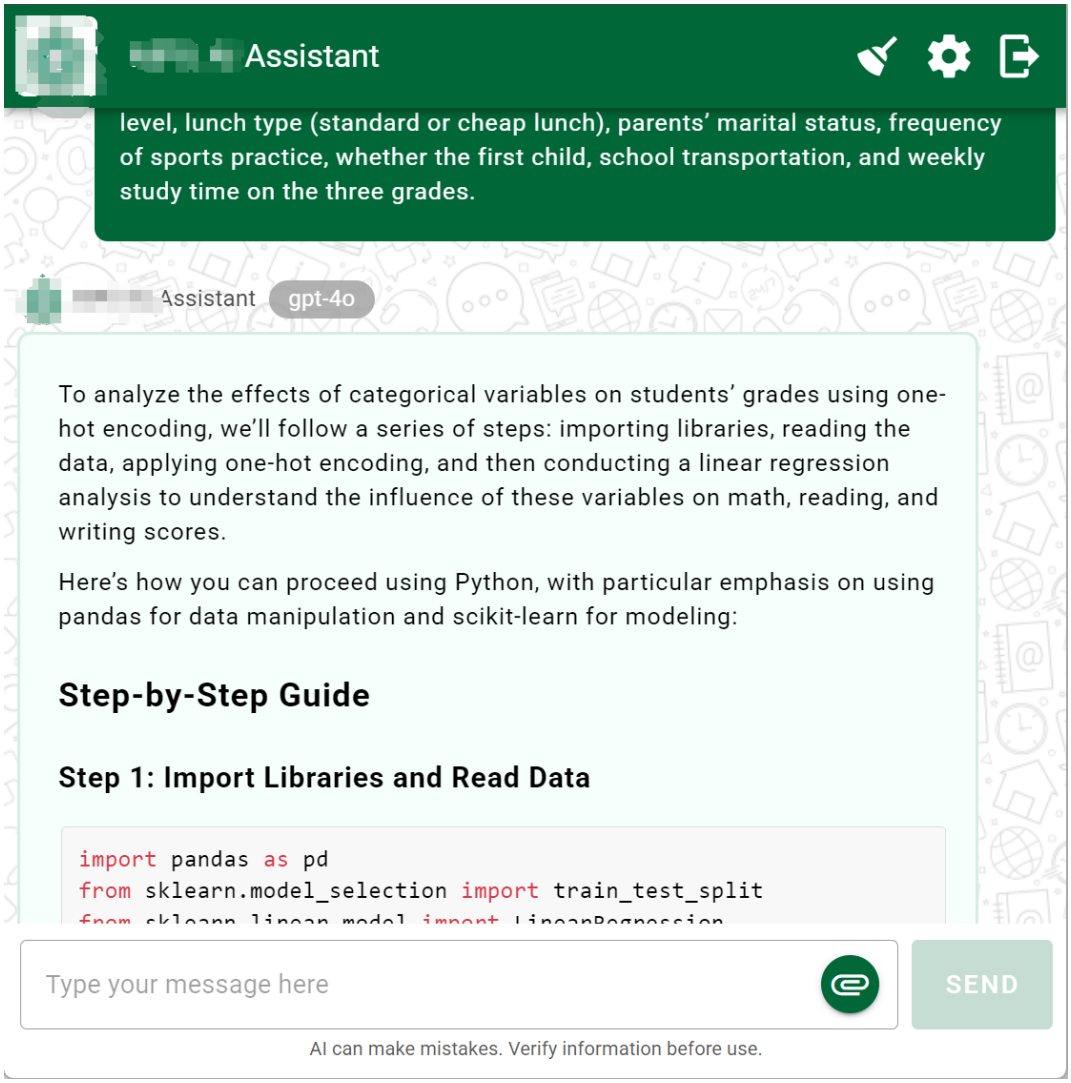

Figure 3. Example of participants using the LLM platform for IBL

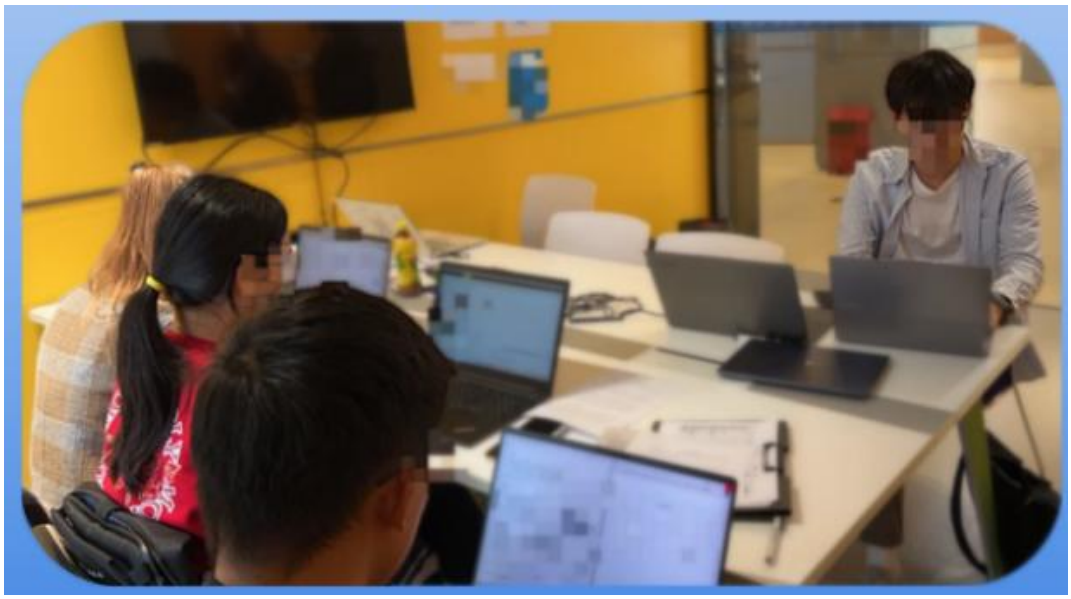

Figure 4. Higher education students participating in IBL experiments

Participants and procedure

This IBL experiment recruited first- to third-year undergraduates from a university in Macao and another in Zhuhai, mainland China. A total of 370 interactive prompts (*M* = 19.47, *SD* = 4.63), 117 retrospectives think-aloud interview transcripts (*M* = 6.16, *SD* = 2.29),and 1,694 minutes of screen recording text (*M* = 89.16, *SD* = 20.20) were collected, involving 19 students. Of the students, 52.6% were male (*N* = 10), and the rest were female. Furthermore, 57.9% of the students were from the School of Science and Technology, 31.6% from the School of Business and the rest from the School of Humanities and Social Sciences.

This study complied with the Declaration of Helsinki (World Medical Association, 2024) and was approved by the Ethics Committee of Macao Polytechnic University (ethics approval no. HEA006-FCA-2025). All procedures adhered to informed consent, data anonymisation and minimal risk principles. Students could freely choose two time slots to conduct the experiments. The experiments were accompanied by the first three of us at the two university sites: Macao Polytechnic University and Beijing Normal University-Hong Kong Baptist University United International College. At each location, we were supported by a local faculty member who assisted with the organisation and logistical arrangements of the sessions. Prior to the IBL task, to ensure that participants had a basic understanding of the LLM and data science, we held a half-hour lecture before the experiment, covering the basic operation of the LLM, basic concepts of data science and basic guidance on IBL. Afterwards, students accessed a web-based experimental platform that contained task description text, data set documentation and an integrated LLM chat environment. Each student completed the task within a self-arranged time period (up to 4 hours). After completion, they submitted their papers through the platform and conducted a retrospective voice interview with us. In this session, students were asked to verbalise their thinking process in IBL while reviewing key excerpts of their conversations with the LLM. In addition, we and a research assistant collected and organised the prompt texts and the retrospective think-aloud interview data, which was then reviewed by a lecturer with a PhD in data science.

Data collection and coding

With the consent of the participants, the interaction records of the prompt word texts of the participants, the think-aloud interview text and the LLM and the screen recordings were saved from each computer. We mainly coded the text data of participants' prompt words and the LLM and retrospective think-aloud interviews, and the behavioural data in the screen recordings were used to assist in verifying the consistency of coding behaviour.

This study adopted a theory-driven thematic analysis method, with Bloom's taxonomy as the core framework, to explore students' behavioural and cognitive patterns of interaction with an LLM in IBL. The overall analysis followed deductive logic while maintaining sensitivity to emerging patterns in the data. The study followed the six-step method of thematic analysis (Braun & Clarke, 2006) and referred to some theoretically oriented thematic analysis coding schemes (Åkerblad et al., 2021). Figure 5 introduces the specific process and details of our theory-driven thematic analysis. After reaching a preliminary consensus on Bloom's taxonomy through discussion, the first two of us (Y.T.L. & T.L.) independently coded the prompt text and interview text (Cohen's kappa: prompt text = 0.81; interview text = 0.74). All disagreements were resolved through discussion and reference to screen recordings. Ultimately, the third one of us (P.P.) integrated the common patterns identified in the codes from both sides. We first performed preliminary deductive coding based on the cognitive dimensions of Bloom's taxonomy, systematically classifying data fragments into a pre-defined theoretical framework. Simultaneously, we maintained an open attitude, inductively labelling and supplementing significant new patterns that repeatedly appeared but may not be covered by Bloom's taxonomy. This hybrid coding approach can enable new insights to be gained quickly in restricted samples by categorising the phenomena described by presupposing the dimensions of Bloom's taxonomy (Houtkoop-Steenstra, 1996).

Figure 5. Parallel thematic analysis coding driven by Bloom's taxonomy

To meet the theoretical maximisation sampling qualitative research, we conducted a pretest to distinguish students who may have diverse characteristics. The pre-test used the General Self-Efficacy Scale for Use with Artificial Intelligence (Morales-García et al., 2024) to assess students' AI abilities and literacy, which included students' use of LLM in assistance, anthropomorphic interaction, AI comfort and technical skills. The design of this study balanced the following two principles: First, in accordance with the spirit of IBL, we avoided formatted scoring to protect students' exploratory autonomy (Hmelo-Silver et al., 2007). Second, based on self-determination theory, we explicitly informed students that their submissions would be reviewed, using this as a form of external monitoring to sustain their engagement motivation (Ryan & Deci, 2000).

To quantitatively describe these differences in cognitive levels among students, we conducted Fisher's exact test on the frequency of occurrence of these stages of Bloom's taxonomy. This statistical test method was performed by creating contingency tables for each cognitive behaviour type. The odds ratio directly quantifies the probability difference between two groups of students exhibiting a certain behaviour, while the p value is used to determine whether this difference is statistically significant.

Once again, though we introduced AI prior knowledge and related frequencies to group students and describe and compare typical cases and behaviours, our goal was not to strictly verify or study the

statistically significant differences in student behaviour adoption or change but emphasise the way students used the LM and their thinking characteristics at different cognitive levels. This was an experimental exploratory study. Therefore, we did not expect to conduct a confirmatory analysis but hoped to gain some insights into the IBL process based on the cognitive stage of Bloom's taxonomy as a valuable perspective.

Results

In this section, we present the results of our study on students' behaviour patterns in the IBL process. Our study was not designed to measure interaction differences or verify theoretical validity but to gain a deeper understanding of students' learning behaviours in the interactive environment of the LLM. Therefore, based on the thematic analysis driven by Bloom's taxonomy, we constructed a coding table for students' behaviours during IBL, as shown in Table 2, and gained a deeper understanding of students' exploration and interaction behaviours.

Table 2
Coding results of the thematic analysis driven by Bloom's taxonomy

Theme	Behaviour type	Behaviour description
Remembering	Precise query	Asking LLM for definitions, terms or background information
Remembering	Fuzzy query	Asking LLM to list a category of objects or facts
Remembering	Knowledge confirmation	Confirming or recalling previously known information
Understanding	Conceptual explanation	Asking LLM to explain a complex concept in plain language
Understanding	Relational understanding	Asking LLM to explain the relationship between two variables
Understanding	Procedural guidance	Asking LLM for guidance on a method or procedure
Applying	Operational request	Requesting LLM to perform or generate step-by-step procedures
Applying	Method application	Asking LLM to apply a specific method to the current data
Analysing	Technical analysis	Exploring data and diagnosing technical issues
Analysing	Conceptual analysis	Analysing logical relationships or methodology
Evaluating	Instrumental judgment	Assessing the suitability of a model or method
Evaluating	Thinking criticism	Critically evaluating logical arguments or research assumptions
Creating	Organisational creation	Using LLM to restructure or optimise existing content
Creating	Integrative creation	Combining multiple sources or methods to generate new insights

Description of experimental subjects

The cognitive levels of Bloom's taxonomy do not necessarily follow a strict linear progression, so there is a phenomenon of cognitive level jumps. Furthermore, not all students show a complete level of Bloom's taxonomy (Lemons & Lemons, 2013). Students often only show certain cognitive levels in actual teaching and assessment, depending on factors including the guidance assigned by the teacher, the students' prior knowledge and the learning context (Krathwohl, 2002; Liu et al., 2014). Because we controlled the scene conditions in the experimental design, we considered the students' factors in practice. Based on the different pre-test results, we divided the students into two categories and re-sorted the student IDs by their level of prior knowledge, with 1–10 students with high prior knowledge and 11–19 students with low prior knowledge. As shown in Figure 6, if the students showed the corresponding Bloom taxonomy stage in the prompt words and interviews, we recorded the corresponding colour. If they do not show the corresponding cognitive stage, the colour was left blank.

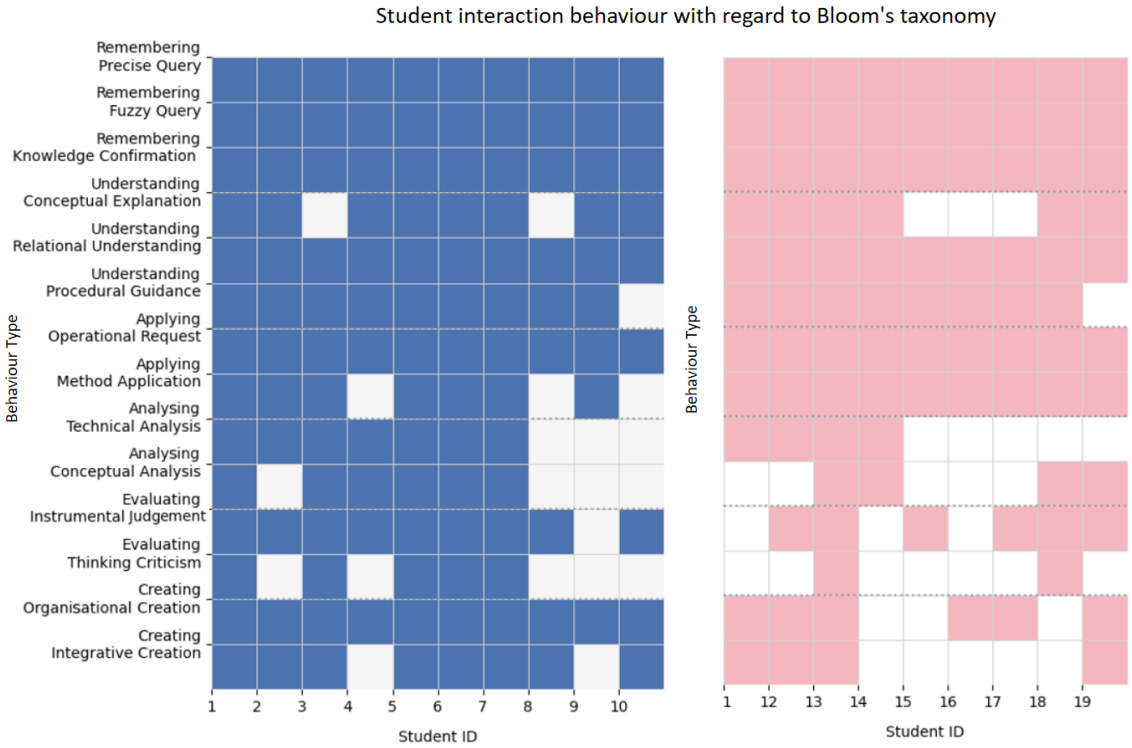

Figure 6. A display diagram of students' cognitive stage behaviours in the thematic analysis

Overall, Fisher's exact test (Nowacki, 2017) showed that different prior levels correspond to basically the same behaviour at the low-level cognitive stage (odd ratio = 0.725, p= 0.749), and there were statistically significant differences in higher-order cognitive behaviours (odd ratio =3.231, p = 0.004).

The interactive behaviour between students and the LLM in IBL

This section introduces examples of student behaviours classified into several types based on coding at different stages to demonstrate unique and interesting interactive patterns in the IBL process.

Remembering

Remembering is described as an objective, primary cognitive behaviour that serves as a preliminary stage of action (Solman & Rosen, 1986). After students read the task requirements and data sets, in addition to importing data into the LLM, most of the actual interaction behaviours of the LLM are to complete the remembering level queries. Precise query refers to students asking direct and clear questions about a concept or method, for example:

> After I finished the statistical analysis of gender, transportation and student performance, LLM recommended that I use machine learning for prediction, but I didn't know what that was, so I looked it up with LLM. [interview]
> What is Machine Learning? [text] (Student 9)

Fuzzy query reflects that students had a preliminary concept of the relevant field but were not clear yet, and they used the LLM to seek answers based on the remaining knowledge in the hope of obtaining a complete and comprehensive explanation or supplement, for example:

> LLM told me the principle of t-test. I remembered there were other test methods, so I asked about it. [interview]
> What other statistical tests are there? [text] (Student 11)

Knowledge confirmation refers to students recalling and verifying based on existing knowledge. This type of behaviour often occured when students verified the original information in a vague or uncertain state, for example:

> I remember learning in class that variables are classified, but I don't remember exactly what type of variable the ride method is, so I asked the LLM. [interview]
> The way of going to school by bus in the data set is a categorical variable, right? [text] (Student 15)

Understanding

The understanding stage emphasises students' interpretation and internalisation of basic information and knowledge. In interacting with the LLM, students not only retrieved information but also began to try to transform knowledge into a form that they could understand. This included how to process data sets, how to analyse and how to select research questions. Concept explanation refers to students asking the LLM to explain a relatively complex or abstract concept in a concise and popular way, for example:

> After I uploaded the data set, LLM told me that I should analyse the standard deviation of students' grades to measure volatility. I don't quite understand this because I may have forgotten some statistical knowledge. [interview]
> why can standard deviation reflect fluctuations? [text] (Student 2)

Relational understanding is manifested as students wanting the reason for the method or the relationship between different concepts, for example:

> What is the difference between a false positive and a false negative? [text] (Student 5)
> Could the interactive relationship between gender and reading time affect final grades? [text] (Student 6)

Procedural guidance reflects students' requests for understanding the logic of the method, reflecting students' desire to know how it works, for example:

> How is the multiple regression logic calculated? [text] (Student 12)

This stage is the largest level in the entire cognitive process involving prompt words, text and interviews. This also shows that in the process of IBL, students constantly encountered cognitive obstacles or problems in the understanding stage. In addition, this stage is also the stage where students' cognitive jumps were most active in the cognitive stage.

Applying

The applying stage emphasises that students use the knowledge or methods they have learned in the LLM to apply them in new scenarios. In our experiment, students gradually applied the research topics and methods determined in the interaction with the LLM to specific data operations, including executing the code learned to clean the data set, using multivariate logistic regression to fit the results and visualising the descriptive results. This stage is mainly divided into two types of behaviours. The operation process request focuses on students asking LLM to provide specific and detailed technical implementation paths:

> LLM gave me a comparison of whether the grades were related to learning confidence under the same learning time, so I wanted LLM to help me generate a code that could run to help me complete it. [interview] (Student 11)

Method application is relatively vague and requires the LLM to directly apply a certain analysis technology to the student's current data background, without specifying the details of the processing:

> Help me make predictions using logistic regression where Y is the grade and the others are X. [text] (Student 9)

Most students directly applied the application in the LLM environment, especially based on the data analysis module built into the LLM in the Python environment. A small number of students used extra data processing software besides the LLM, including R, or online data analysis websites such as SPSSAU (https://spssau.net/). Students who used a variety of software for applications interacted less with the LLM during this cognitive stage than other students. This is because, in addition to the difference in prior knowledge levels, the challenges of the LLM platform itself for the data analysis environment and installation package loading also made most students who used the LLM only for application spent a lot of time debugging.

Analysing

Analysing means that students actively explore information structure, variable relationship or model logic in the task, and conduct critical thinking with the help of the LLM. Technical analysis is manifested as students using the LLM to help identify technical problems in the application process, including problems with the data or abnormal performance of variables, for example:

> After running the regression, I noticed some variables had extremely high p-values. I asked LLM why this might happen, and it suggested checking for multicollinearity. [interview]
> Why does my multiple linear regression show some coefficients with $p > 0.15$? Is there a problem with my data? [text] (Student 9)

Conceptual analysis is manifested as students using LLM to help think about theoretical or conceptual problems, for example:

> I wasn't sure if my data met the normality assumption for ANOVA, so I asked LLM what alternatives exist if the assumption is violated. [interview]
> Can I still use ANOVA if my data is skewed? What are the robust alternatives? [text] (Student 18)

Evaluating

Evaluating means that students judge the rationality and effectiveness of methods, hypotheses or data results, which helps them examine their own learning process and outcomes. Instrumental judgement focuses on the applicability and effectiveness evaluation of techniques and methods and it has a clear operational objective and emphasises the comparison of the pros and cons of methods, for example:

> I am not satisfied with the results of my linear regression run. I want to use more methods to see the results. [interview]
> Which is better for predicting students' performance? logistic regression or random forest? [text] (Student 3)

Thinking criticism refers to observable interaction behaviours in which students explicitly question or challenge the logic and theoretical assumptions underlying their papers or proposals, for example:

> I used ANOVA, but LLM pointed out that unequal variances could bias results. I then asked how to check for heteroscedasticity. [interview]
> Does ANOVA require equal variances across groups? What if my Levene's test is significant? [text] (Student 6)

It should be pointed out that an important manifestation of the evaluating stage in LLM-driven IBL is the continuous questioning of the results, which runs through the entire IBL process. In particular, the hallucinations created by the LLM aggravate the degree of students' questioning and objectively promote the generation of such evaluation behaviour, for example:

> The things I made based on LLM are indeed very efficient and seem to be perfect, but I always feel something is wrong, which makes me keep asking LLM about the details of my

> methods and results to see if I have made any mistakes. I can only feel at ease if I keep asking. [interview] (Student 6)

Creating

Creating is the highest level of Bloom's cognitive taxonomy. With the support of LLM, the interactive behaviour is reflected in the reconstruction of all previous materials, cross-domain integration, and innovative exploration of expression methods. Organisational creation is manifested as students requesting LLM to reorganise and optimise existing content, and it is more difficult to categorise and predefine. This kind of behaviour always brings people more universal inspiration, for example:

> I asked a lot of questions before, so I asked LLM to help me integrate the previous questions. [interview]
> Rewrite my methodology part and integrate the content you gave me according to the logic I asked you. [text] (Student 9)

Integrated creation represents a more complex cognitive activity. This type of innovation includes many organic combination behaviours, for example:

> LLM told me that the performance criteria of the model should be based on different actual situations. I wonder if we can take MSE and robustness into consideration at the same time. [interview]
> Combine MSE and robustness, with half the weight, as the loss function of random forest? [text] (Student 2)

Discussion

LLMs provide an excellent platform and space for students to engage in IBL, especially in informal learning contexts where teacher guidance may be limited (Wiese & Magana, 2024). In this study, we analysed and categorised students' behaviours during IBL with the LLM based on different stages of cognitive engagement, offering insights for educators to design more adaptive IBL tasks.

Low-order cognitive stage

We found that the full range of behaviours in the remembering stage was not determined by prior knowledge level. Regardless of whether they had high or low prior knowledge, all students demonstrated these three behaviours in the remembering stage when facing new learning tasks. This also indirectly shows that the interaction behaviour in the remembering stage is a normal state between students and the LLM during the IBL process.

In the understanding stage, some students at both levels of prior knowledge showed a lack of conceptual explanation-related behaviours, and we found that there were differences in the reasons behind these two deficiencies. Students with low prior knowledge showed apprehension towards challenging tasks using the LLM for research and a lack of enthusiasm for exploration. On the other hand, students with higher prior knowledge were usually able to clearly articulate their thinking and core concepts at the beginning of the interview, so when interacting with the LLM, they no longer needed to rely on its output to gain basic conceptual understanding.

This may reveal the influence of self-efficacy on behaviour at the cognitive stages. Self-efficacy related to LLMs has been shown to have a profound relationship with students' cognitive skills and engagement behaviours (Kwak et al., 2022; Sökmen, 2021). Students with high self-efficacy are more confident in proactively setting learning goals, adjusting strategies and skipping or omitting steps, when necessary, when interacting with the LLM. Such students are also more likely to initiate the self-monitoring process, conduct self-assessment and adjustments in learning and display typical characteristics of self-regulated learners (Bozkuş & Canoğulları, 2025; Sufyan Ghaleb & Alshiha, 2023). This characteristic is also reflected

in the applying stage. One student (Student 4) skipped the application of the model using the LLM for the same reason and instead used his statistical software for calculations.

High-order cognitive stage

Overall, all students' higher-order cognitive behaviours were lower than those in the previous stages. From the results of the behavioural pattern survey, we found that the reasons for behavioural deficits in different advanced cognitive stages are different. In the analysing stage, the primary limitation lies not in a lack of exploratory ability but rather in insufficient motivation for autonomous exploration, which often manifests as cognitive inertia, such as active avoidance of complex information processing. In the evaluating stage, it is more due to the defects in metacognitive awareness and reflects the immaturity of self-monitoring ability. In the creating stage, it is manifested as the combined effect of many factors.

Relatively speaking, students with low prior knowledge lack more high-order cognitive behaviours. Weaker self-efficacy students are more likely to develop AI reliance in the absence of sufficient background knowledge support. They rarely consider strategies or plan for independent exploration, such as what to do first and what to do next. They often rely on the LLM to automatically generate content after randomly inputting questions, because they are vague about the goals they need to achieve. In such cases, their behaviours are limited to a low cognitive level.

Such dependent use of LLM may not only result in superficial learning but also limit the development of students' enthusiasm for exploration and metacognitive abilities (Biswas & Murray, 2024; Zhai et al., 2024). To address this issue, it is vital to emphasise the development of students' metacognitive monitoring skills, which are a key bridge between surface-level interaction and deep cognitive engagement (Biswas & Murray, 2024; Sasson & Tifferet, 2025). When students have well-developed metacognitive strategies, they are more likely to engage in deeper, purposeful interactions and complete higher-quality, complex, cross-disciplinary inquiry tasks with the power of LLMs (Goyal, 2025; Khotimah & Rusijono, 2024). Conversely, students with rich prior knowledge exhibit higher engagement in higher-order cognitive stages. This is partly reflected in their strategic use of prompt design. These students frequently employ techniques such as requiring logical reasoning or iteratively refining questions (e.g., Student 6). Such well-designed prompts serve as an external tool for metacognitive control, directly supporting their higher-order thinking. In the classification in Bloom's taxonomy, this ability to design advanced prompts is correlated with behaviours in conceptual analysis and thinking criticism. The ability to design effective prompts is not merely a technical skill but also a tangible manifestation of metacognitive awareness and critical thinking, enabling students to strategically navigate the LLM to achieve complex cognitive goals.

Implications

Based on the above findings, we propose the following implications for educational practice and policy:

Implement differentiated teaching interventions

Educators should design cognitive scaffolding based on students' prior knowledge levels. For those with weak foundations, a guiding prompting framework focusing on understanding and application should be provided; for those with stronger foundations, challenging tasks designed to stimulate analysis, evaluation and creation can be designed. The key is to explicitly integrate metacognitive strategies and prompting engineering skills in teaching. For example, guiding students to actively engage with the LLM to provide higher-level feedback, such as designing a Socratic-style agent to train and enhance self-regulation. In addition, we strongly recommend that educators design educational interventions and cognitive scaffolding that explicitly teach metacognitive strategies when promoting students to use the LLM for IBL tasks, including guided planning frameworks (Chang et al., 2023; Prasad & Sane, 2024) and iterative feedback evaluation (Jha et al., 2023; Shah et al., 2021), which are particularly effective in promoting meaningful AI-assisted learning. By enhancing learners' self-monitoring and regulation capabilities, they

can gradually overcome their dependence on AI, thereby helping to ensure that the LLM truly empowers cognitive abilities and becomes a driving force for students to explore in the face of rapid changes and heavy information overload.

Innovate the assessment system and ensure technical fairness

Educational institutions need to promote the shift of the assessment paradigm of IBL from outcome-oriented to process-oriented, focusing on the thinking processes and problem-solving iteration abilities demonstrated by students in their interactions with the LLM. At the same time, it is necessary to formulate inclusive digital literacy training policies to ensure that students with limited AI literacy can also master the core skills for efficient collaboration with AI, such as basic prompting engineering, to curb the new digital divide caused by the gap in technical skills.

Conclusion

The practice of using LLMs is reshaping the way students conduct IBL and handle complex tasks. This study explored how students use LLMs for IBL at different cognitive stages. We used thematic analysis based on Bloom's taxonomy and combined with coding frequency to reveal different student behaviour patterns in using the LLM for IBL. However, this study has some limitations. Our study aimed to initially understand and explore students' IBL behaviour in an LLM-driven learning environment. It is difficult to clarify the causal relationship between certain specific behaviours, such as cue design, and behaviours like thinking criticism. As another limitation, this study recorded only one IBL course and may not reflect the impact of long-term behavioural changes and cognitive levels of LLM-assisted learning. Furthermore, our study did not establish a correlation between LLM-driven environments and mentoring and thus may lack an assessment of the unique impact that the LLM environment may have. In future, we plan to conduct quantitative research with a larger sample size and add objective dimensions such as eye movement data to comprehensively analyse students' interactive behaviours in exploratory learning during long-term experiments.

Author contributions

Yiming Taclis Luo: Conceptualisation, Methodology, Validation, Formal analysis, Data curation, Writing – original draft; **Ting Liu:** Validation, Investigation, Data curation; **Patrick Pang:** Writing – review & editing, Supervision, Project administration, Funding acquisition; **Dana McKay:** Writing – review & editing; **Shanton Chang:** Writing – review & editing; **George Buchanan:** Writing – review & editing.

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