DEVELOPING AI LITERACY THROUGH DIGITAL MAKING: A STUDY ON STUDENTS' CONCEPTUALIZATIONS OF AI AND SHIFTS IN UNDERSTANDING DATA'S ROLE

Huiyan Ye[1], Oi-Lam Ng[2], Zhihao Cui[1]
[1]The Education University of Hong Kong, [2]The Chinese University of Hong Kong

AI literacy has gained growing significance in K-12 education, with an urgent need to explore how to integrate AI literacy into mathematics classrooms. Underpinned by constructionism, this study designed a three-phase AI lesson themed around machine learning from a regression perspective. Three themes emerged in students' conceptualizations of AI after the lesson: the learning process of AI, AI's capabilities and the role of data in developing AI models. Furthermore, students' understanding of data's role shifted markedly from a general focus on data as input or data quantity to a heightened emphasis on data quality. The findings contribute to a deeper understanding of how data literacy develops within an AI context and will inform both theory and practice for integrating AI literacy into K-12 mathematics education.

INTRODUCTION

Artificial intelligence (AI) is transforming the ways we communicate, work, and interact with one another and with machines (Long & Magerko, 2020). This transformation underscores the significance of AI literacy for all individuals. As AI decision-making relies on mathematical models and data, the integration of AI literacy in mathematics education provides opportunities for students to understand the nature of AI technology and its underlying ethical and societal implications from a mathematical perspective, such as examining the data origins of algorithmic bias. This lays the foundation for developing critical thinking, rationally assessing technological risks, and cultivating responsible digital citizenship (OECD, 2025). Therefore, integrating AI literacy into K-12 mathematics education holds particular relevance.

To this end, we explored an integrated approach tailored to secondary mathematics education, aiming to facilitate integration of AI's technical and conceptual knowledge to co-develop students' mathematical literacy and AI literacy. Specifically, by utilizing user-friendly AI platform *Machine Learning for Kids* (ML4K), alongside programming tool *Scratch* and mathematics-specific tool *GeoGebra*, we designed a series of rich learning activities. These activities support students in constructing their personal AI artefacts while enabling them to experience and understand the learning mechanisms of AI models and their underlying mathematical principles through hands-on making. Therefore, this study aims to investigate the following research question: What aspects of AI literacy do students develop through these activities? Specifically, (1) How do students conceptualize AI after learning? (2) What shifts occur in their understanding of the role of data in AI model development?

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THEORETICAL FRAMEWORK

AI Literacy and Data Literacy in K-12 Education

Long and Magerko (2020) defined AI literacy as "a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace" (ibid, p. 598). To structure this literacy, they proposed a conceptual framework consisting of five overarching themes (What Is AI?; What Can AI Do?; How Does AI Work?; How Should AI Be Used?; and How Do People Perceive AI?) and outlined a corresponding set of AI competencies, e.g., Competency 1 (C1) Recognizing AI: Distinguish between technological artifacts that use and do not use AI. Moving beyond Long and Magerko's (2020) competency-focused conceptualization, the OECD (2025) proposes an updated definition of AI literacy structured around knowledge, skills, attitudes and competences. This reframing conceptualizes AI literacy as "the technical knowledge, durable skills, and future-ready attitudes required to thrive in a world influenced by AI," empowering individuals "to engage, create with, manage, and design AI, while critically evaluating its benefits, risks, and ethical implications" (p. 6). As highlighted by OECD (2025), students' conceptual knowledge of AI is interwound with their AI competences. The technical and societal understandings (e.g., how AI processes data, and how bias can emerge in AI systems) support learners engage with AI systems; while designing AI empowers students understand AI's societal and ethical impacts.

Data literacy also constitutes a core component of AI literacy. Within Long and Magerko's (2020) thematic module How Does AI Work, five competencies are particularly pertinent to data literacy: C8 (Decision-Making), C9 (ML Steps), C11 (Data Literacy), C12 (Learning from Data), and C13 (Critically Interpreting Data). Given that machine learning (ML) is a cornerstone concept and data forms the foundation of AI, emphasizing the role of data within AI contexts is crucial for developing students' data literacy.

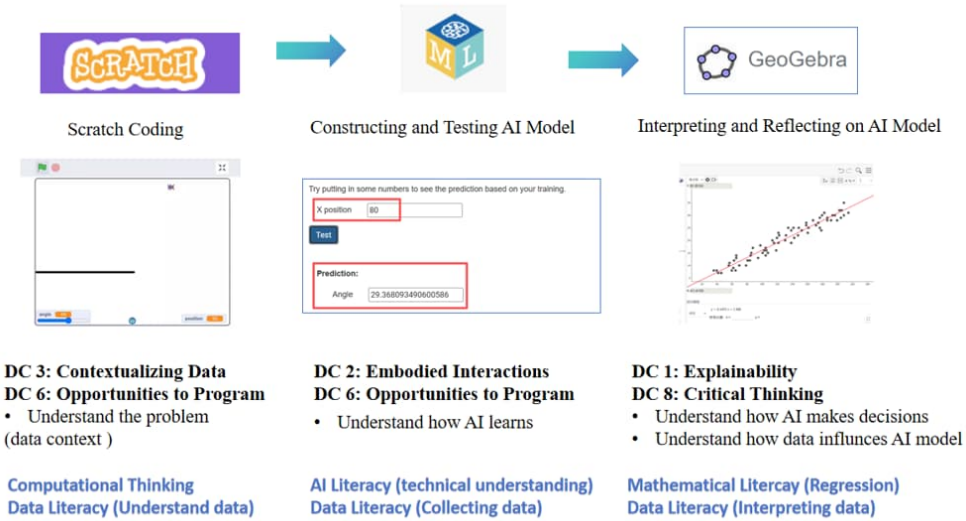
Constructionism and Digital Making: Learning-by-making

Proposed by Seymour Papert (1991), constructionism posits that the most productive learning occurs when learners create a personal, shareable artefact that serves as an "object-to-think-with," facilitating the construction of coherent cognitive structures (i.e., Learning-by-making). Building on this, Ng and Cui (2021) conceptualize "digital making" as a form of constructionist learning, wherein students actively construct mental schemas while constructing digital artefacts. Furthermore, Lin et al. (2025) identifies five core learning mechanisms in constructionist environments that support the development of students' AI literacy, which emphasize (1) employing constructionist tools as cognitive tools, (2) internalizing AI knowledge through embodied cognition, and (3) fostering epistemic practices.

Therefore, underpinned by constructionism, this study integrated user-friendly programming tool *Scratch* and AI platform *ML4K* to engage students in exploring ML

by constructing their personal AI models. Moreover, drawing on the *Explainability* design consideration (DC)—which entails incorporating visualizations, simulations, explanations of agent decision-making processes, and interactive demonstrations to enhance learners' comprehension of AI (Long & Magerko, 2020)—we integrated GeoGebra to generate scatter plots and lines of best fit using data collected for AI model training. This integrated approach enabled students to visualize and understand how AI learns and makes decisions from a mathematical regression perspective, thereby fostering their mathematical literacy, data literacy, and AI literacy (Figure 1).

Figure 1. Lesson design considerations and learning objectives



METHOD

Participants and Context

Situated in a larger design-based research project (Ng et al., minor revision), this study was collaborated with a secondary school in Hong Kong. Framed as an extra-curricular course, it involved a class of Grade 10 students (n=34). The entire course lasted for about 2.5 hours and was delivered in a computer laboratory. All students sat in rows and worked independently on computers while following the lesson content, and they were also allowed to discuss with adjacent peers at the same time. Prior to the course, informed consent was obtained from both students and their parents.

Research Design

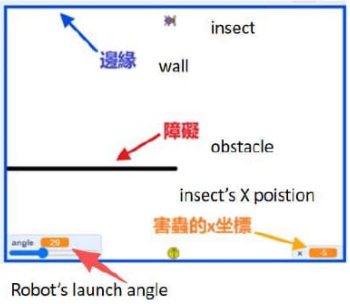
The course was primarily designed to engage students in an AI literacy integration activity themed around ML. The task design integrated the affordances of three digital tools—Scratch, ML4K, and GeoGebra—to guide students in exploring the working principles, mathematical essence, and limitations of AI models through regression fitting, while fostering their reasoning about how AI learns and makes decisions based on data (Ng et al., minor revision). Centering on a core task of empowering a robot to hit a target insect at an optimal angle via AI prediction (Figure 2), the course was structured into three sequential phases.

Figure 2. The problem context for the lesson

Problem Context:

An insect and cleaning robot are in the room. When the robot touches the walls and obstacle, it will bounce off.

Please try to program the robot to successfully catch the insect.



Phase 1: Scratch simulation experiments

In the first phase, students were tasked with assembling Scratch blocks to program the robot to perform bouncing behaviors, where the robot would bounce off walls and obstacles upon contact, and attempt to catch the target insect. They then optimized the program by randomizing the insect's X-coordinate and the robot's launch angle, conducting multiple random simulations to observe the low hit rate in unassisted trials (*DC 3: Contextualizing Data; DC 6: Opportunities to Program*). During this process, we posed guiding questions to trigger thinking: "What do you think AI is, and how may AI help us solve this problem?" These questions were intended to facilitate students recognize AI's role and influence in solving real-world problems.

Phase 2: Constructing an AI prediction model

The second phase began with a discussion exploring the differences between AI and non-AI systems, as well as the role of data in supporting AI operations. We first defined the relationship between the "insect's X-coordinate" and the "robot's launch angle" to clarify the data dimensions for model training. Students then added data collection blocks in Scratch to record a large set of valid ordered pairs [(insect's X-position, robot's launch angle)] from successful hits, generating a comprehensive training dataset (*DC 3; DC 6*). Next, they uploaded the dataset to the ML4K platform to train a simple prediction model (*Designing AI competences*). Upon completing model training, students revisited their Scratch program, integrating the trained model to predict launch angles for several randomized insect positions, thereby enacting AI-assisted target hitting (*Engaging with AI competences; DC 6*). Guiding questions were designed to prompt students to reflect on the model's performance in terms of prediction accuracy and identify potential avenues for improvement. This activity aims to provide students opportunities to explore how AI systems can be designed to support a solution, and evaluating the potential benefits, risks, and limitations (*Designing AI competences*).

Phase 3: Interpreting and reflecting on AI models via Regression

The third phase focused on unpacking the AI model's mathematical essence via regression analysis interpretation. Students uploaded their pre-acquired training dataset into GeoGebra for scatter plot generation, then analyzed data patterns and identified

the line of best fit. This activity guided them to explored the underlying mechanism of AI decision-making, including how the model selects an optimal regression model for collected data and predicts launch angles using given inputs and the derived function (*DC 1: Expainablitity*). Guiding questions were posed to facilitate their sense-making of the relationship between linear regression and AI models, such as (a) In this AI model, what are the features (inputs) and what are the labels (outputs)? (b) What does the "line of best fit" in the graph represent, and how is it used to enable AI "learning"? (c) Why do not all data points lie exactly on this line? In the closing part of the lesson, the class engaged in a discussion about the limitations of the trained AI model and proposed potential optimization strategies (*DC8: Critical Thinking*).

Data Collection, Processing and Analysis

To investigate students' prior understanding of AI, a pre-test was administered at the start of the lesson. This pre-test included open-ended questions and multiple-choice items related to AI literacy, e.g., "What is the role of data in developing an AI model?" At the end of the lesson, we also collected students updated understanding of AI and the role of data by assigning a course reflection featuring open-ended questions, e.g., Please share your understanding of AI in as much detail as possible.

Regarding data processing, deductive and inductive coding approached were employed to analyse students' development of AI literacy. Specifically, we categorized students' conceptualization of AI by drawing on the detailed set of AI literacy competencies for learners as outlined by Long and Magerko (2020). As for RQ2, thematic analysis (Braun & Clarke, 2006) was adopted to examine shifts in their understanding of the role of data in developing AI models. A dedicated coding scheme was developed (see Table 1) to facilitate the systematic analysis of RQ2.

Table 1. Coding scheme: understanding of the role of data in developing an AI model

Code	Level Name	Description	Examples
1	Data as Input	Views data merely as raw material for AI learning.	*AI learns through data.* (E1 Pre-test)
2	Quantity Determines Accuracy	Emphasizes the impact of data "quantity" on the accuracy of the AI model.	*The more data AI collects, the more it benefits accuracy.* (C4 Post-test)
3	Quality Determines Accuracy	Recognizes the role of data "quality" on the accuracy of the AI model	*If the data is erroneous, the result will also be inaccurate*. (F1 Post-test)

RESULTS

RQ1: Students' conceptualization of AI

Based on students' course reflection, three themes of their conceptualization of AI were identified: the learning process of AI, AI's capabilities and the role of Data.

Theme 1: AI's Learning Process

The first theme centers on the core developmental workflow of AI systems. The analysis reveals that students developed an understanding of AI learning as data-

driven, iterative process. They emphasized the importance of collecting specific, high-quality data rather than generic datasets with their conception of data evolving from an abstract notion of "big data" to concrete, task-relevant "successfully validated data" (G1). Students also recognized that AI identifies inherent "patterns" or "proportional relationships" within datasets to inform its functionality (D1). The term "model" was also clearly defined by students as both the product of AI learning and a functional tool for real-world applications—for instance, regarding models as instruments for "making predictions" (G3) or "increasing success rates" (G2). Overall, students demonstrated three key competencies: they recognized AI systems learn from data (*C12: Learning from Data*); developed a clear understanding of the steps involved in ML (*C9: ML Steps*); and acquired foundational data literacy concepts encompassing data collection and analysis (*C11: Data Literacy*).

Theme 2: AI's Capabilities (Speed and Potential)

K1: I used to think AI could only create, calculate, and find information—I never expected it to be so useful after learning.
K2: I witnessed AI's learning speed firsthand; AI can learn data immediately.
L2: It made me realize that AI learns very fast.

The second theme aligns with the module focus What Can AI Do, and students' reflections conveyed surprise at the breadth and efficiency of AI's capabilities. These insights indicate that students were developing Competency 5 (Recognizing AI's Strengths & Weaknesses). Specifically, they demonstrated an emerging ability to recognize AI's strengths in performing specific tasks (e.g., content creation, calculation, information retrieval), moving beyond their initial narrow perceptions to appreciate AI's broader utility (K1). Additionally, students were able to recognize the high efficiency inherent to AI's learning mechanisms, as evidenced by K2 and L2's observations regarding AI's rapid data-processing speed. These growing awareness of AI's potential and performance characteristics represents a foundational step toward determining when to leverage AI as opposed to human skills, thereby facilitating students' competence in engaging meaningfully with AI systems.

Theme 3: The Role of Data (Focusing on Data's Impact on AI Performance)

E1: AI is not entirely accurate; it draws conclusions based on different data.
G2: The more accurate data AI has, the better results it can achieve.
G3: I understand the training process of AI models and also realize how incorrect data during training can affect the model.

The third theme situated within the module *How Does AI Work*, with a focus on the impact of data on AI development and performance. Students' understanding of AI evolved beyond the basic premise that "AI learns from data" to a nuanced understanding of "the relationship between data quality and the accuracy of AI models". Their recognition that "training data impacts AI model performance" reflects their development of data literacy and AI literacy. Specifically, students demonstrated an understanding of data's pivotal role in AI learning (E1; *C12: Learning from Data*);

developed a critical perspective on data usage (G2; *C11: Data Literacy*); and how the quality and relevance of training examples in an initial dataset can influence algorithmic outcomes (G3; *C13: Critically Interpreting Data*), which marks a more comprehensive understanding of AI's operational mechanisms and decision-making processes. A detailed analysis of how students' understanding of data's role in AI development shift will be presented in the subsequent section in responded to RQ2.

RQ2: Students' Shift in Understanding of the Role of Data

A comparison of students' pre-test and post-test responses reveals a notable shift in their understanding—from a general focus on data as input or data quantity to a heightened emphasis on data quality (Table 2).

Table 2. Examples of students' understanding of the role of data

Student	Pre-test	Post-test
J2	**1 (Data as Input)**: Provide more information for AI training	**2 (Quantity Determines Accuracy)**: Helps AI have more accurate answers.
E1	**1 (Data as Input)**: AI learns through data.	**2 (Quantity Determines Accuracy)**: Increase accuracy.
D1	**2 (Quantity Determines Accuracy)**: More data leads to more powerful, correct output.	**2 (Quantity Determines Accuracy)**: The more effective data provided, the more precise the AI.
F1	**1 (Data as Input)**: Use different data to organize and conclude.	**3 (Quality Determines Accuracy)**: If the data is wrong, the result will also be inaccurate.
E2	**1 (Data as Input)**: Absorb practical experience.	**3 (Quality Determines Accuracy)**: If the data is correct, it operates normally.

As shown in Table 2, students advanced from the vague conceptualization of "data as input" to a targeted recognition of data's impact on "AI model accuracy", thereby identifying the significance of *data quantity* in constructing high-performing AI models (J2, E1). While students such as D1 retained their core understanding at Level 2, the inclusion of the keyword "effective" in their post-test responses reflects an emerging focus on *data quality*, signalling a developing awareness of how data quality shapes AI learning outcomes. On the other hand, a substantial increase was observed in the number of students who recognized the critical impact of data quality on AI model outcomes. Multiple students explicitly stated in the post-test that data correctness or inaccuracy directly determines whether an AI model operates reliably or produces erroneous outputs (F1, E2), revealing their critical comprehension of AI's working mechanism. Through hands-on construction of AI models, students no longer perceived AI as an inscrutable "magic black box"; instead, they developed an understanding that AI outputs are highly contingent on the quality of the input data.

Furthermore, the analysis identified a refined understanding among students regarding the dual (positive and negative) impacts of data relevance in AI system development. When training data was highly revenant, students characterized it as "learning material" (L1) or "training material" (C1) for AI, emphasizing its core function in enhancing model accuracy and performance. For instance, one student noted, "Data allows AI to draw conclusions and can increase AI' success rate" (G2). In contrast, when confronted with irrelevant data, students acknowledged that flawed or non-relevant datasets would

cause AI to "become confused" (K1), yield inaccurate results (F1), or generate operational errors (E2). This dichotomous insight reflects a holistic understanding of the fundamental nature of AI learning: AI systems extract patterns from training data regardless of whether those patterns are valid or erroneous. Collectively, these findings indicate that students began to conceptualize data—encompassing both quantity and quality—as the foundational source from which AI constructs internal knowledge frameworks and decision-making rules.

CONCLUSION

This study integrated AI competencies (Long & Magerko, 2020) with the OECD's (2025) AI literacy framework, focusing on AI conceptual knowledge (i.e., ML processes) and high-level practices (data gathering, model training, testing, prediction) to foster students' AI and data literacy. Through hands-on inquiry in a problem-solving context, students explored how data influences AI system accuracy—an initiative emphasizing "learning-by-making" and aligned with Long and Magerko's (2020) DCs. Specifically, it addresses DC 6 (Opportunities to Program): enabling individuals to program/teach AI agents while minimizing coding prerequisites via diverse teaching strategies; and DC 2 (Embodied Interactions): designing interventions for individuals to "put themselves in the agent's shoes" to interpret its reasoning, including algorithm simulations and hands-on AI experimentation. Additionally, Low Barrier to Entry (DC 15) is strongly advocated as a critical principle for teaching AI concepts to K-12 students. Future research is encouraged to further explore these DCs to advance the integration of AI literacy into K-12 mathematics education.

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