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Empowering K-12 Education with AI

Preparing for the Future of Education and Work

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Instructional Designs for AI Interdisciplinary Learning

Four

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Instructional Designs for AI Interdisciplinary Learning

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Interdisciplinary learning in schools breaks down subject barriers, allowing students to explore real-world problems through multiple lenses, fostering collaboration, creativity, and a deeper understanding of the interconnectedness of knowledge.

Thomas K. F. Chiu

4.1 INTRODUCTION

Artificial intelligence (AI) is an interdisciplinary domain, drawing upon knowledge and techniques from various fields such as mathematics, computer science, biology, psychology, neuroscience, linguistics, sociology, and philosophy (Allen & Kendeou, 2024; Doroudi, 2023; Gibson et al., 2023; Zhuang et al., 2020). The development of AI technologies requires experts from various disciplines. For example, mathematics serves as the fundamental basis for the development of algorithms and models used in AI (Davis, 2024; Hesami & Jones, 2020); psychology aids in understanding how human intelligence works and its potential replication in machines (Dong et al., 2020; Lindsay, 2020). Moreover, AI literacy is related to other literacies like data, mathematics, reading, and science (Casal-Otero et al., 2023; Long & Magerko, 2020; Stolpe & Hallström, 2024). Implementing AI education through an interdisciplinary approach is a logical and inherent choice (Baum, 2021; Chiu, 2023, 2024; McCrum, 2017; Ramos et al., 2020).

An interdisciplinary approach provides a number of benefits that enhance both the learning experience and the development of essential skills for students (Cooper et al., 2001; Jimenez et al., 2022; Lattuca et al., 2017; Yahya & Hashim, 2021). It better develops the following skills of students.

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- **Holistic understanding:** By integrating knowledge from various disciplines, students develop a comprehensive understanding of complex topics. This holistic approach helps them see the interconnectedness of different fields and how they contribute to broader issues.
- **Lifelong learning mindset:** This approach nurtures a love for learning and curiosity that extends beyond traditional disciplinary boundaries. Students become lifelong learners, continuously seeking connections and expanding their knowledge across various disciplines.
- **Real-world relevance:** Interdisciplinary learning connects subject knowledge and concepts to real-world applications, enhancing students' understanding of how knowledge can be applied in practical contexts. This prepares them for future careers where they may need to navigate interdisciplinary challenges.
- **Versatility and adaptability:** Students become versatile and adaptable learners who can apply their knowledge and skills in various contexts. They become comfortable navigating complexity, embracing ambiguity, and seeking innovative solutions.
- **Collaboration and communication skills:** Working on interdisciplinary projects often requires collaboration with peers from different backgrounds. This promotes effective communication, teamwork, and the ability to work harmoniously in diverse groups, mirroring real-world professional environments.
- **Creativity and innovation:** Exposure to diverse disciplines sparks creativity. Students are more likely to generate innovative ideas when drawing on a range of knowledge areas. This mirrors the collaborative nature of many creative and innovative endeavors in the professional world.
- **Critical thinking skills:** Students learn to grasp main ideas, compare and contrast knowledge from different subjects, and develop critical thinking skills. This promotes higher-order thinking and the ability to analyze complex problems from multiple perspectives.
- **Complex problem-solving skills:** Interdisciplinary learning equips students with the ability to tackle complex problems using multidimensional approaches. They learn to draw on diverse knowledge and methodologies to develop creative strategies and solutions.

However, in K-12 AI education, computer science teachers or technology coaches are the primary teachers; other subject teachers are not involved. This lack of integration of AI across subject areas can limit students' exposure to the field and hinder their ability to see the connections between AI and other disciplines. With the involvement of teachers from various subjects in the teaching of AI, students can better understand how AI can be applied in different contexts and how it relates to their other subjects.

Therefore, this chapter uses operational and cognitive perspective to suggest how to design and assess AI learning using interdisciplinary approaches. We present an operational interdisciplinary framework describing how various subjects get involved. The framework guides you to engage different subject teachers in contributing to AI education. Then we present a three-level cognitive relationship that elucidates various literacies (such as digital, mathematical, and computational) in relation to AI literacy. Understanding the cognitive processes involved in AI literacy can provide you insights into how students learn and apply AI knowledge, concepts, and skills in real-world scenarios. Both operational and cognitive perspectives could make a significant contribution, helping teachers and researchers understand the complexities of student AI learning and development. In addition to these guidelines, we also present and discuss three practical strategies for non-AI and AI teachers to integrate AI into their subject teaching using interdisciplinary approaches.

4.2 OUR OPERATIONAL INTERDISCIPLINARY FRAMEWORK FOR AI

AI is an interdisciplinary field that includes mathematics, computer science, biology, psychology, neuroscience, linguistics, sociology, and philosophy (Allen & Kendeou, 2024; Doroudi, 2023; Knoth et al., 2024). Nevertheless, the prevailing perception among teachers in schools is that AI is primarily a subject related to technology. This implies that the teaching of AI is integrated into the curriculum of technology education (Stolpe & Hallström, 2024). Technology teachers bear the exclusive duty of cultivating students' AI literacy and competency. This phenomena might be likened to the belief held by certain teachers that the responsibility for fostering students' digital competency lies only with a specific set of technology teachers (Chiu et al., 2024; Falloon, 2020; Stolpe

& Hallström, 2024). AI education in K-12 should involve teachers from various subjects, ensuring an interdisciplinary approach (Allen & Kendeou, 2024; Falloon, 2020).

To simplify terminology for teachers and students, we refer to AI as an inter-teaching subject, instead of interdisciplinary domain. The teaching subjects that contribute to AI include mathematics, computer science, science, language, social studies, music, and economics, as depicted in Figure 4.1. Psychology, neuroscience, and philosophy were eliminated because they are less common in K-12. Linguistics and sociology were renamed as language and social studies, respectively. Music was added to address the vocal aspects of AI topics like computer speech or voice recognition, which require an understanding

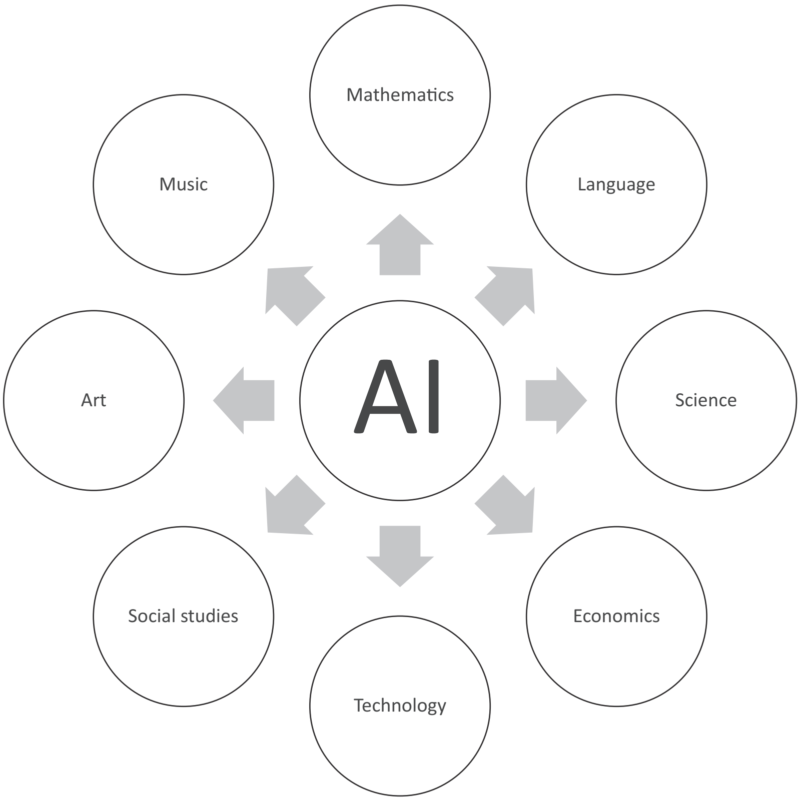


Figure 4.1 AI as an inter-teaching-subject approach in K-12 (interdisciplinary)

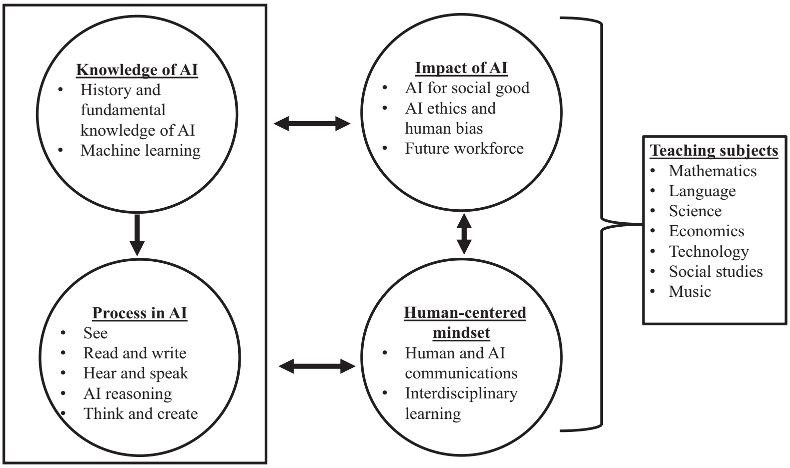


Figure 4.2 Our operational interdisciplinary framework for K-12 AI education

of characteristics like pace, pitch, and frequency. The inter-teaching subject approach provides a distinct framework for non-technology teachers to contribute to the development of student AI literacy and competency.

In the operational interdisciplinary framework (see Figure 4.2), there are four main knowledge entities: knowledge of AI, process in AI, impact of AI, and human-centered mindset. The framework suggests that (i) knowledge of AI is the prerequisite of process in AI, and both entities are viewed as technical knowledge of AI; (ii) the impacts of AI and a human-centered mindset are mutually dependent and related; (iii) the impacts of both AI and a human-centered mindset interact with the technical knowledge of AI; and (iv) all teaching subjects should contribute to the four knowledge entities. Table 4.1 shows the topics in each entity and their suggested teaching subjects.

- **Knowledge of AI:** Topics include History and Fundamental Knowledge of AI, as well as Machine Learning. This entity is aligned with learning data in the four studies (Allen & Kendeou, 2024; Chiu, 2021; Chiu et al., 2022; Touretzky et al., 2019, 2023). On the topic of Fundamental Knowledge of AI, students should learn about big data, cloud computing, applications of AI, deep learning,

Table 4.1 The contributions of various teaching subjects to the interdisciplinary framework

Entity	AI topics	Descriptions	Possible teaching subjects
Knowledge of AI (learning from data)	History and fundamental knowledge of AI	Big data, cloud computing, applications of AI, deep learning, neural network, unsupervised learning, supervised learning	Technology, mathematics
	Machine learning	Google Teachable Machine and other machine learning tools, collect data	Technology
Process in AI (perceptions)	See	Computer vision, face detection, face recognition	Technology, science
	Read and write	Natural language processing, natural language understanding	Technology and language
	Hear and speak	Factors affecting voices, text-to-speech, speech-to-text	Technology, science, music
	AI reasoning	Rule-based reasoning, skill-based reasoning, knowledge-based reasoning	Technology
	Think and create	Artificial general intelligence, generative AI	Technology
Impact of AI	AI for social good	How AI is being used to solve real-world problems	Social studies
	AI ethics and human bias	Ethical principles, the role of humans in AI ethics	Social studies
	Future workforce	How will AI affect jobs	Social studies, economics
Human-centered mindset	Human and AI communications	Human and AI interfaces, human and AI interaction	Technology, language, social studies
	Interdisciplinary learning	Creation of solution for real-world problems	Non-technology

neural networks, unsupervised learning, and supervised learning. The suggested teaching subject is technology. In Machine Learning, students should learn how to collect data and use Google Teachable Machine and other machine learning tools to create machine learning applications. The suggested teaching subjects are technology and mathematics.

- **Process in AI:** There are five topics concerning perceptions. The first topic is See, which is related to computer vision, face detection, and face recognition. The suggested teaching subjects are technology and science. The second topic is Read and Write, which is related to natural language processing and natural language understanding. Its suggested teaching subjects are technology and language. The third topic is Hear and Speak, which is related to factors affecting voices, text-to-speech, and speech-to-text. Its suggested teaching subjects are technology, science, and music. The fourth topic is AI Reasoning, which includes rule-based reasoning, skill-based reasoning, and knowledge-based reasoning. The fifth topic is Think and Create, which is related to artificial general intelligence and generative AI. Due to their technical nature, the suggested teaching subject for the last two topics is technology only. These topics were derived from the curriculum framework suggested by Chiu and colleagues (2022).
- **Impact of AI:** This entity has three topics. The first topic is AI for Social Good. Students should learn how AI is being used to solve real-world problems. The second topic is AI Ethics and Human Bias. Students should understand ethical principles, and the role of humans in AI ethics. The suggested teaching subject for these two topics is social studies. The last topic is Future Workforce. Students should learn how AI would affect jobs. Its suggested teaching subjects are social studies and economics. These topics were suggested by most of the existing studies (Allen & Kendeou, 2024; Chiu, 2021; Chiu et al., 2022; Touretzky et al., 2019, 2023).
- **Human-centered mindset:** This entity has two topics. In the first topic, Human and AI Communications, students should learn about human and AI interfaces, as well as human and AI interaction. The suggested teaching subjects are technology, language, and social studies. In the second topic, Interdisciplinary Learning, students should create solutions for real-world problems. Non-technology subjects are the suggested teaching subjects.

Overall, our interdisciplinary framework offers an operational perspective to promote collaboration among different subject teachers to foster student AI literacy and competency. This is achieved by explicitly identifying the recommended teaching subjects. While this framework proposes seven subjects, it is important to note that additional subjects can also contribute to interdisciplinary AI education (Allen & Kendeou, 2024; Chiu et al., 2024; Falloon, 2020).

4.3 OUR THREE-LEVEL COGNITIVE RELATIONSHIP

The analysis of AI learning can be approached from a cognitive perspective, as demonstrated in the study conducted by Long and Magerko (2020). The development of literacy is based on cognitive processes (Botting, 2020; Casal-Otero et al., 2023; Kravchenko, 2021; Markauskaite et al., 2022). Hence, understanding the interconnections between different literacies and AI literacy from a cognitive perspective enhances our knowledge of interdisciplinary learning in AI (Sabatini et al., 2023).

Literacy was originally defined as the ability to express oneself and communicate through written language (Norris & Phillips, 2003). This term refers to skill sets for using, applying, and communicating in a variety of disciplines, including mathematics, sciences, digital, and data (Casal-Otero et al., 2023; Chiu & Sanusi, 2024; Chiu et al., 2024; Long & Magerko, 2020; Stolpe & Hallström, 2024). Understanding the interrelationships between different literacies and AI literacy enables teachers and researchers to understand the direct and indirect literacies of AI (Sabatini et al., 2023).

Figure 4.3 shows our three-level cognitive interrelationship describing how various literacies relate to AI literacy. There are three levels of interrelationships: close, intermediate, and distant. Four literacies have close relationships with AI literacy: data, digital, mathematics, and scientific literacy. First, data literacy is a subfield of machine learning (Elshawi et al., 2018; Long & Magerko, 2020) and refers to the ability to use data effectively and responsibly in any content within an iterative inquiry cycle (Gummer & Mandinach, 2015; Markham, 2020). This literacy largely overlaps with AI literacy, particularly in machine learning and ethics. Second, digital literacy refers to the ability to appropriately access, use, and evaluate digital resources, tools, and services for communication and learning (Chiu

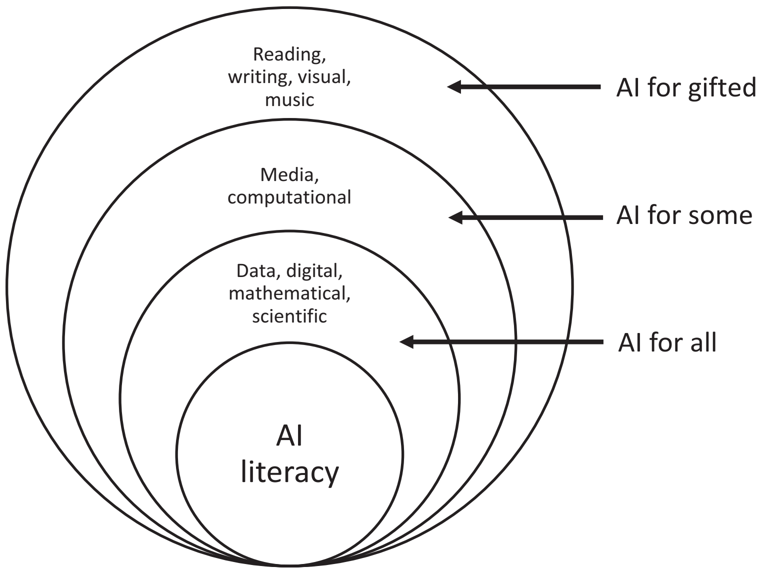


Figure 4.3 Our three-level cognitive interrelationship describing how various literacies relate to AI literacy

et al., 2024; Falloon, 2020). AI is a form of digital resource, and so digital literacy is a prerequisite for AI literacy. Third, mathematical literacy refers to the ability to formulate, apply, and interpret mathematics in a variety of contexts (Kilpatrick, 2001; Ozgen, 2019). It includes using mathematical reasoning and concepts to explain and predict phenomena. AI basic knowledge is rooted in mathematics, and so mathematical literacy is a prerequisite for AI literacy (Kong et al., 2024; Long & Magerko, 2020; Sperling et al., 2024). Finally, scientific literacy refers to the knowledge and understanding of scientific concepts and processes that are essential for making personal decisions (Norris & Phillips, 2003; Smith et al., 2012). It includes the process of posing, discovering, or determining solutions to everyday problems, as well as the ability to describe, explain, and predict natural phenomena. Scientific literacy informs AI literacy, particularly understanding machine learning practices such as supervised learning (Long & Magerko, 2020).

We suggest media and computational literacy have an intermediate relationship with AI literacy, and are important for critically analyzing

AI-related data and information and developing AI applications. Media literacy refers to the ability to access, analyze, and evaluate media messages, as well as to create, reflect, and act across a variety of contexts (Alvermann & Hagood, 2000; Schwarz, 2005). Given the popularity of generative AI and artificial general intelligence, more fake news and videos are likely to be created and spread in the future (Chu-Ke & Dong, 2024; Raman et al., 2024). This poses a significant threat to society as it becomes increasingly difficult to discern what is real and what is fabricated. To combat the spread of misinformation, students should become more media literate and critical of the information they see. This implies that media literacy is related to the impact of AI; media literacy is relevant to, but not completely necessary to, AI literacy. Moreover, computational literacy refers to the ability to formulate problems, represent their solutions as computational steps and algorithms, and use coding skills to create and evaluate the solutions (Grover & Pea, 2013; Long & Magerko, 2020; Wing, 2006). Using coding skills to create AI applications is for AI developers, not users. Not all the students are developers. Coding education can be a major learning barrier for some students (Long & Magerko, 2020). Most students only interact with, but do not develop, AI in their daily lives, and so computational literacy, while closely related to AI literacy, is not necessarily a prerequisite.

We further suggest that reading, writing, visual, and sound literacy have distant relationships with AI literacy. Reading and writing literacy are components of linguistic literacy, which is the foundation of natural language processing and natural language understanding technologies (Castillo et al., 2023; Green, 2019; Sabatini et al., 2023). They are related to the topics Read and Write (natural language processing). Students with higher levels of reading and writing literacy may have a greater understanding of how language works, including sentence grammar and structure. They can better comprehend the algorithms and processes used in natural language processing technology (Castillo et al., 2023; Green, 2019). They may also be able to more effectively design models for machines to read and write. However, not all students are required to understand all the sophisticated mechanisms for how AI processes language. Moreover, visual literacy refers to the ability to interpret, negotiate, and make meaning from information presented in the form of an image (Hailey et al., 2015; Níkleva & Rodríguez-Muñoz, 2022). Students with stronger visual literacy could better understand visual cues and patterns. They better collaborate with machines to analyze and interpret large sets of visual data, leading to a better understanding of processes in computer vision. Therefore, they have advantages when learning the topic See (computer vision). Furthermore, music literacy is the ability to perceive, perform, and compose music, as well as an understanding of cultural practices and their social and historical contexts (Broomhead, 2021; Stakelum, 2024). Students with stronger music literacy may have a greater understanding of the aspects that determine how people speak, such as emotions and ages, as well as voice characteristics such as pitch and frequency, and the sounds of various instruments. Therefore, they have advantages when learning the topics Hear and Speak (computer speech and voice recognition). Students with strong visual and music literacy can convey meaning and evoke emotions in various forms of audio and visual. They can effectively communicate ideas and messages through digital media. Overall, students with stronger reading, writing, visual, and music literacy can better develop some aspects of AI, particularly for process in AI and perceptions (Chiu, 2021; Chiu et al., 2022; Touretzky et al., 2019, 2023).

Overall, we believe that the relationships between different literacies and AI literacy might provide valuable guidance to teachers and researchers in designing interdisciplinary AI learning. We recommended that teachers and researchers use a differentiated curriculum to accommodate the interrelationships between literacies (Ruys et al., 2013; Xia et al., 2022), namely AI for all students, AI for some students, and AI for gifted students (see Figure 4.3). For example, it is important to prioritize the development of AI literacy for all students, along with fostering data, digital, mathematical, and scientific literacy. Students with stronger learning abilities can be offered learning activities on how media and computational literacy relate to AI literacy. Gifted students can benefit from more learning about how reading, writing, visual, and music literacy relate to AI literacy.

4.4 PRACTICAL STRATEGIES FOR INTERDISCIPLINARY TEACHING WITH AI

Aside from the operational and cognitive perspectives, we provide three practical strategies for interdisciplinary teaching with AI, which will assist teachers in integrating AI into non-AI subject teaching. To develop the three strategies, we collaborated with 50 middle and high school teachers from a variety of major teaching areas to create learning tasks for leveraging machine learning to teach non-AI subjects.

The first two strategies are to foster interdisciplinary learning by creating and unpacking machine learning models. Machine learning educational tools are more accessible to K-12 students and teachers (Sanusi et al., 2023; Su et al., 2023; Tedre et al., 2021). Students could collect data such as images, sounds, and motion to train their own machine learning. The strategies are (i) classification and generalization skills and (ii) unpacking models. The latter strategy viewed AI as authoring digital tools and resource providers. Students used generative AI tools, such as ChatGPT, text-to-images, text-to-videos, and text-to-slides, to create multimedia resources and get knowledge from other disciplines for interdisciplinary learning. We refer to this strategy as alternative intelligence (i.e., using generative AI to get second opinions or create multimedia resources).

4.4.1 Classification and Generalization Skills

Classification and generalization skills are fundamental to human learning and are linked but distinct cognitive skills (Kraiger et al., 1993; Kuhn et al., 2000; Rodriguez & Tamis-LeMonda, 2011). Effective learning requires the ability to classify examples into appropriate categories and generalize knowledge to new circumstances (Seger & Peterson, 2013). It involves extracting general principles, rules, or patterns from specific examples or experiences (Erickson & Kruschke, 1998; Renkl, 2024). Students' ability to classify new examples and apply their knowledge to new contexts is influenced by their prior knowledge and experience (Day et al., 2015; Nam & McClelland, 2024).

To be more specific, classification skill involves assigning new examples to predefined categories, while generalization skill is the ability to extend knowledge to new contexts or problems (Nam &

McClelland, 2024). Classification skill is a specific type of learning task, while generalization skill is a broader cognitive process that underlies different types of learning (including classification) (Kraiger et al., 1993; Nam & McClelland, 2024; Seger & Peterson, 2013). Classification skill is assessed based on accuracy, while generalization skill is assessed based on the ability to apply knowledge in new contexts. For example, students with strong classification skills would be able to sort and organize mathematics sequences based on the specific criteria they had learned, while those with strong generalization skills would be able to transform an unknown sequence into something they know for sorting and organizing or revise the criteria. As a result, these two skills in human learning (e.g., cognitive development and critical thinking) are similar to machine learning in AI.

Classification and generalization skills are essential in creating machine learning models (Dargan et al., 2020; Hackeling, 2017; Kotsiantis et al., 2006). To create a model, students are required to categorize data into different classes based on specific features or attributes (classification skill). This enables machine learning algorithms to learn patterns and make predictions or decisions based on new data input. For example, in animal image recognition, a machine learning model can be trained to classify images of different animals based on specific features such as fur color and shape of ears. In spam email filter, a model can be trained to classify emails based on their content, such as address domains and titles commonly used in spam.

Generalization in machine learning refers to the ability of a model to perform well on new and unseen data after being trained on a limited set of data. Students' generalization skills are associated with their disciplinary knowledge and experience (Kraiger et al., 1993; Nam & McClelland, 2024; Seger & Peterson, 2013). Therefore, students with stronger generalization skills have broader views about a discipline, including more classes or categories when training a model. For example, students with weaker generalization skills may train a model using animals with sitting poses only, whereas those with stronger generalization skills include animals in different poses. The model trained by the weaker students may not accurately identify animals in different poses, leading to errors in its predictions. Students' prior knowledge of animals has direct associations with generalization skills (Day et al., 2015; Nam & McClelland, 2024). This implies that

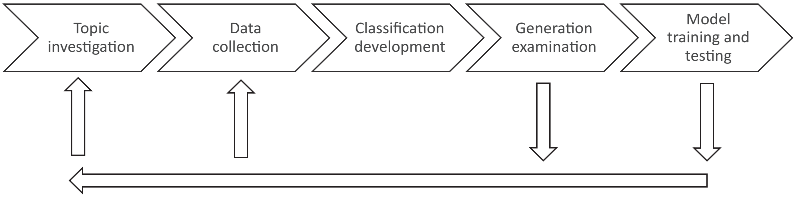


Figure 4.4 An iterative cycle for learning through training machine learning models

training and teaching a machine learning model requires solid disciplinary knowledge, not just technical skills (Rosé et al., 2019). Training and testing machine learning models can develop student classification and generation skills in a subject domain.

Accordingly, to foster student learning of a topic using machine learning, we present a five-stage iterative cycle comprising topic investigation, data collection, classification development, generation examination, model training, and testing (see Figure 4.4). Students actively research a topic to gain a better understanding (Topic investigation) and then collect various sets of data based on their understanding (Data collection). They use the collected data to identify features and attributes for defining classes (i.e., categories) (Classification development). Students identify cases that are unlikely to be included in the defined classes (Generation examination). If there are any cases, students should return to either topic investigation (when they believe they need to learn more about the topic) or data collection (when they can collect data to represent the cases). These stimulate critical thinking about data, rather than just relying on the built-in algorithm. Finally, students use the data and defined classes to train and test their machine learning models (model training and testing).

Case study 1 Learning sciences using machine learning (using classification and generation skills)

Students learn biology by training a model to identify the sex of animals. Table 4.2 displays some of the activities that students engage in during the five-stage learning cycle. Students used

Table 4.2 Student activities during the five-stage learning cycle

Stage	Activities
Cycle 1	
Topic investigation	Students used biological differences between male and female cats (i.e., genitals).
Data collection	Students collected pictures of cats with and without testicles.
Classification development	Students categorized the pictures into male (with testicles) and female (without testicles) cats.
Generation examination	Students undertook further study, and found that some male cats do not have visible testicles, for example, young kittens under development. The skills of cross-validation and regularization may be involved.
Cycle 2	
Topic investigation	Students undertook further study, and found the following: Color: The color patterns of cats are sex-linked. For example, calico (a tricolor pattern in black, white, and orange) tortoiseshell (a mottled pattern of swirled color in back and orange) are more likely to be seen in female cats; and 80% of orange cats are male (because of chromosomal patterns).
Data collection	Students collected more pictures to address the new discovery.
Classification development	Students revised the classification and categorized the pictures into male and female cats.
Generation examination	Students found that some pictures may not be able to identify some cats that did not have the color patterns such as white and orange.
Cycle 3	
Topic investigation	Students undertook further study, and found the following: Distance of two orifices in the rear: A male cat's penis is lower, and the testicles are located between the penis and the anus, but a female kitten's vulva is a vertical elongated orifice near the anus; i.e., cats have two orifices (penis/vulva and anus) that are close together in the rear. When the orifices are further apart, the cat is a male.
Data collection	Students collected more pictures to address the new discovery.
Classification development	Students revised the classification and categorized the pictures into male and female cats.
Generation examination	Students could not find any new exceptional examples.
Model training and testing	Students trained their machine learning models with the pictures collected, and tested the models with new pictures.

their classification and generation skills throughout machine learning model training. At the stage of generation examination, students heavily execute their critical thinking skills to revise the classes by identifying some new situations.

Case study 2 Learning middle school mathematics for machine learning

A decision tree is a technique for classifying cases that requires mathematical reasoning and thinking. This implies that students can better prepare for the training of machine learning models by cultivating this technique. The worksheet that the teachers have prepared is shown below. The purpose of the worksheet is to enhance the classification skills of students by facilitating the creation of decision trees. On the worksheet, the first three phases of the cycles are addressed by Questions 1, 2, and 3a, while the fourth stage is addressed by Question 3b.

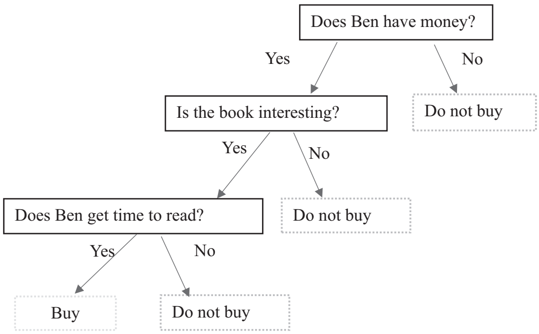
Decision tree worksheet (mathematics)

Decision trees are useful tools for organizing and guiding our decision-making and activities in our daily lives.

Key idea:

- One method for representing all possible outcomes of a set of decisions is to use a decision tree.
- A decision tree is a tree-like model that represents decisions and their potential outcomes.

Question 1: The following is a decision tree to determine whether Ben should buy a book. Study it to see if you understand the tree by giving some examples.



Question 2: Create a decision tree to describe your decision and action after schools.

Question 3a: Draw a decision tree to determine the grade of mangoes using the following table.

Question 3b: Use new data sets to test the tree.

Label ID	Weight (g)	Color	Black mark	Grade
1000001	Larger than or equal to 300	Yellow	No	A
1000002	Larger than or equal to 300	Yellow	Yes	D
1000003	Larger than or equal to 300	Green	No	B
1000004	Larger than or equal to 300	Green	Yes	D
1000005	Smaller than 300	Yellow	No	C
1000006	Smaller than 300	Yellow	Yes	D
1000007	Smaller than 300	Green	No	C
1000008	Smaller than 300	Green	Yes	D

Case study 3 Learning health sciences using machine learning

Students learn health science by training a model to categorize a meal into levels of healthiness. Table 4.3 shows some of the students in the final stage of the learning cycle. Similar to Case study 1, students use their classification and generation skills throughout machine learning model training.

Table 4.3 Student activities in the final stage of the learning cycle

Stage	Activities
Final cycle	
Topic investigation	Students used the color and area of a meal on a plate to categorize the meal into levels of healthiness.
Data collection	Students collected pictures of different meals on plates.
Classification development	Students categorized the pictures into five levels of healthiness (5=very healthy, 1=very unhealthy).
Generation examination	Students undertook further study and concluded how colors (different types of food) and portions (areas) related to level of healthiness.
Model training and testing	Students trained their machine learning models with the pictures collected, and tested the models with new pictures.

We used a pre- and post-test approach to examine whether the students could gain a better understanding of disciplinary knowledge in all three case studies. The numbers of students involved were 160, 172, and 145 in Case studies 1, 2 and 3, respectively. The results of paired t-tests showed the students had significantly improved their knowledge in the sciences, $t\ (159) = 5.2$, $p < .001$, mathematics, $t\ (171) = 4.5$, $p < .001$, and health sciences, $t\ (144) = 4.1$, $p < .001$. In addition to these three case studies, we also designed activities for other topics, including (i) learning sport sciences by determining whether a motion is correct in yoga; (ii) learning culture by identifying traditional clothes; and (iii) learning language by identifying thesaurus words or creating spam email filters.

By creating machine learning models that can generate new ideas, students can experiment with combining knowledge from different subjects in innovative ways (Chiu & Li, 2023; Ramos et al., 2020; Tedre et al., 2021). This not only encourages connecting different subject knowledge but also helps students develop a holistic understanding of how various subjects can intersect and complement each other (Ramos et al., 2020). Through the process of designing and training machine learning models, students gain valuable experience in problem-solving, critical thinking, and creativity, skills that are essential for success in any interdisciplinary field (McCrum, 2017).

4.4.2 Unpacking Models

This strategy involves the reverse thinking of classification and generation skills. Instead of collecting data to train a machine learning model, students uncovered how data and outputs related to each other. By revising thinking, students challenge traditional learning and explore alternative learning that involves a lot of back-and-forth thinking (Pittalis et al., 2020; Spaan et al., 2024; Weng & Chiu, 2023). Unpacking a machine learning model involves (i) exploring, (ii) examining, and (iii) explaining the structure, parameters, and algorithms of predictive models to understand how they make predictions or classifications (Biecek & Burzykowski, 2021; Burrell, 2016). By dissecting the model's inner workings, students can gain insights into the underlying patterns and relationships in the data that the model has learned. This unpacking process helps to uncover the features and variables that are most important for the model's decision-making and helps to understand how to adapt to unseen data. This process can also help identify any biases or shortcomings in the model that may need to be addressed. Therefore, unpacking a machine learning model allows for a deeper understanding of the subject matter being studied.

We suggest that students should explore, examine, and explain the machine learning model developed by their peers. They can seek alternative perspectives to improve their own models. Students have become more familiar with the context (i.e., disciplinary knowledge) (Kraiger et al., 1993; Nam & McClelland, 2024; Seger & Peterson, 2013). In addition, we suggest that students explore, examine, and explain how rule-based chatbots interact with humans. The rule-based model is much less complex than a large language model. In other words, it is more affordable for young students to learn with a rule-based model (Williams & Wood, 2015). The interactions of a rule-based model often rely on certain keywords and phrases (classification skills). Through understanding the interaction, students can acquire language proficiency and get insight into the specific context in which chatbots operate. For example, students can enhance their language proficiency and geographical knowledge by analyzing chatbots that provide information about train stations. We believe students were encouraged to suggest ways to improve the chatbots (generalization skills).

4.4.3 Alternative Intelligence

In order to promote student interdisciplinary learning, the first two strategies focused on the use of machine learning models. The third and last strategy focused on the use of generative AI tools, such as ChatGPT, text-to-images, text-to-videos, and text-to-slides, to connect various disciplines. Generative AI tools serve as an alternative intelligence and help students complete some tasks they feel they cannot do (i.e., using generative AI to get second opinions or create multimedia resources). We worked together with the teachers to propose the following four opportunities.

- **Encourage cross-disciplinary integration:** Generative AI tools can synthesize knowledge from multiple disciplines, identify interdisciplinary connections, and offer insights that bridge different disciplines (Kusters et al., 2020; Peters et al., 2023). They enable students from different disciplines to collaborate on projects by combining their diverse knowledge and skills (Chiu, 2023, 2024; Chiu & Li, 2023; Chiu et al., 2023; Cooper & Tang, 2024). For example, in STEAM education, students who are weak at coding can develop simple applications by asking GitHub Copilot, which generates specific code suggestions including variables, classes, and methods based on their situations (Chiu & Li, 2023). Those who are poor in art design can use text-to-images to generate visuals. The use of generative AI can foster interdisciplinary STEM learning (Chiu & Li, 2023; Cooper & Tang, 2024). Overall, students can use the tools to complement the knowledge gaps they have because they have instant access to information and resources related to other disciplines (Kusters et al., 2020; Peters et al., 2023).
- **Facilitate critical thinking for real-world problems:** Real-world problems require students to develop solutions by considering multiple disciplines (Lachney et al., 2021; Zhang & Chan, 2023). Generative AI tools facilitate students in tackling complicated, practical problems by proposing new ideas, solutions, and unnoticed connections across several disciplines. With the aid of the tools, students can explore and create solutions that involve several disciplines through the use of research, analysis, and generating content (ElSayary, 2023; Peters et al., 2023). For example, students

can use ChatGPT to obtain new insights by asking for an outline of the fundamental elements of a problem; they can receive feedback from ChatGPT regarding their proposed solutions; and they can use ChatGPT to summarize their diverse disciplinary ideas (ElSayary, 2023; Peters et al., 2023). These activities broaden student understanding of the problem and improve their critical thinking, empowering them to more efficiently address complex real-world problems that span multiple disciplines (Lachney et al., 2021; Zhang & Chan, 2023). Overall, the tools make interdisciplinary learning more accessible and manageable (Pahi et al., 2024). They facilitate students' ability to recognize interconnections among various disciplines; thereby, students feel comfortable with ambiguity and complexity. In other words, with the help of the tools, students believe they can engage in collaborative work with others from various disciplines and effectively convey their ideas across different disciplines (Chiu, 2024; Chiu & Li, 2023; Pahi et al., 2024). They cultivate a diverse set of abilities and attributes, including receptiveness to new ideas, critical thinking, and forward thinking, which prepare them to have a constructive impact on the world.

- **Serve a variety of roles to assist students in completing their projects:** (i) authoring assistants who develop multimedia resources such as posters, movies, infographics, and slide shows (Chiu, 2024; Chiu & Li, 2023; Das et al., 2024); (ii) editors who edit their work and transform it into any writing style: technical, casual, or advertisement (Alyasiri et al., 2024); (iii) translators who can translate their work into any language or convert articles published in an unknown language to a language they can read; (iv) virtual tutors who can provide students with tailored instruction and support while they construct prototypes or products (Chiu, 2024; Chiu & Li, 2023; Park & Ahn, 2024). For example, students can use generative AI tools to develop campaigns for various audiences in different regions. They are expected to express their solutions using a variety of forms and languages. These technologies can help students with research, analysis, and ideation, promoting interdisciplinary learning through hands-on experiences. Overall, generative AI tools are personal learning assistants for students in project-based learning.
- **Foster creativity and innovation:** Generative AI promotes open-mindedness, creativity, and innovation by offering multiple perspectives

and solutions that transcend disciplinary boundaries (Chiu, 2024; Chiu & Li, 2023; Dwivedi et al., 2021; Houssaini et al., 2024; Kanbach et al., 2024). This pushes students to think outside the box, challenge traditional methods, and investigate innovative interdisciplinary solutions (Chiu & Li, 2023; Houssaini et al., 2024). Students are encouraged to explore new ideas, experiment with different approaches, and collaborate with peers from diverse backgrounds. These foster a culture of continuous learning and growth, resulting in interesting and new discoveries across a variety of disciplines.

4.5 CONCLUSIONS

This chapter advocates for the use of an interdisciplinary approach to integrating AI in K-12 education. We use the AI competency frameworks for students (proposed in Chapter Two) and teachers (proposed in Chapter Three) to propose an interdisciplinary framework for AI education in K-12. This operational framework provides teachers and researchers with valuable insights into how to effectively engage various subject teachers in teaching AI, by clearly defining the teaching subjects. The explicit suggestion is to clearly state the teachers' responsibility for avoiding confusion or disagreement. Taking a cognitive perspective into account, we use a three-level relationship to describe how different literacies relate to AI literacy and explain how the relationships connect to interdisciplinary learning. The operational and cognitive approaches can help us better understand how students learn AI in an interdisciplinary way.

Finally, we offered three strategies—classification and generalization skills, unpacking models, and alternative intelligence—to use AI tools for student interdisciplinary learning. The first strategy offers a five-stage iterative cycle comprising topic investigation, data collection, classification development, generation examination, model training, and testing (see Figure 4.4). The second strategy offers the procedure of unpacking a machine learning model—exploring, examining, and explaining. The last strategies suggest that generative AI serves as alternative intelligence and offers four opportunities.

AI education should be conducted via interdisciplinary approaches, as these approaches can help students connect across subjects and create a more holistic understanding of complex concepts. Students become more adaptable, open, flexible, and innovative in their thinking. This helps them to develop creativity, critical thinking, and problem-solving skills. The interdisciplinary approaches also encourage curiosity and a willingness to explore new ideas, both of which are critical skills for success in the AI era, better preparing students to address real-world challenges and achieve in a range of disciplines.

Actions you may consider taking

- Discuss with your curriculum leaders how to incorporate AI into classrooms.
- Use the operational framework to assign instructional tasks, and then use the cognitive perspectives to develop learning activities.
- Design your differentiated curriculum based on the three-level cognitive interrelationship: AI for all students, AI for some students, and AI for gifted students.
- Use the first two practical strategies to design instructions with machine learning tools.
- Use the third practical strategy to design interdisciplinary project-based learning.
- See AI as alternative intelligence when integrating AI into learning and teaching.
- Emphasize classification and generalization skills when incorporating machine learning in instruction.

Questions you may ponder

- How can we evaluate the design of interdisciplinary AI curriculum?
- How can we apply our three-level cognitive interrelationship to practice?
- How can we examine the effectiveness of different frameworks for AI education in K-12?
- How can we design assessments that effectively evaluate student learning when machine learning is used in instructional designs?
- Does prior subject knowledge influence student learning through machine learning? If so, how?

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