MetaCoXAI Framework: Linking XAI, Computational Thinking, and Metacognition for Learning

Gi Woong Choi[1,†], Sang Won Bae[2,*,†]

[1]University of Cincinnati, TEACHER-DYER 615K, 2610 McMicken Cir, Cincinnati OH 45221, USA
[2]Stevens Institute of Technology, 1 Castle Point Terrace, Hoboken, NJ 07030, USA

Abstract

Despite growing interest in artificial intelligence in education, there remains a notable research gap concerning how AI, specifically explainable artificial intelligence (XAI), can potentially support and enhance students' metacognitive abilities and computational thinking (CT). To bridge this gap, we propose MetaCoXAI, a novel conceptual framework that integrates XAI with computational thinking instruction, offering actionable strategies for learners to develop a deeper understanding of AI processes. Grounded in interdisciplinary theoretical insights from learning technologies, human-computer interaction, machine learning, and XAI, MetaCoXAI explicitly targets the four fundamental components of computational thinking: abstraction, decomposition, algorithm design, and debugging. The framework illustrates how XAI facilitates these CT processes, thereby positively influencing learners' metacognitive skills. To demonstrate the practical utility and application of our proposed framework, we provide research directions highlighting how learners can utilize XAI-supported computational thinking to enhance both problem-solving proficiency and AI competency.

Keywords

Metacognition, Computational Thinking (CT), Explainable Artificial Intelligence (XAI), Abstraction, Decomposition, Algorithms, Debugging

1. Introduction

With the growing popularity of AI, its potential for innovation in the field of education is tracking attention [1]. Furthermore, due to the widespread usage of AI across various aspects of society, encounters with AI technology have become increasingly common in our daily lives, extending beyond computer science professionals. For instance, despite being available to the public for a short period of time, ChatGPT [2] is being widely utilized by students for their studies and assignments, yet discussions of appropriate educational usage and ethical issues remain underexplored, which calls for more discussions on the effective and ethical uses of AI technologies in educational settings. Although there has been progress in terms of implementing AI for education, existing AI-based learning systems often lack transparency in their decision-making processes, which limits students' understanding of how AI functions. Moreover, these systems rarely provide explicit support for developing learners' metacognitive and computational thinking skills which are essential competencies for navigating the increasingly complex, technology-driven world. Therefore, there is a critical gap in effectively leveraging AI to cultivate deeper learning experiences and cognitive skills.

To bridge this gap, we propose a novel conceptual framework that connects computational thinking (CT), metacognition, and explainable artificial intelligence (XAI). Metacognition can be defined as "cognition where the information on which a learner operates describes features of cognition" [3]. Metacognition is critical for students' learning processes, leading to improved performance and productivity. It has played an important role in learning domains such as attention [4], problem solving

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*Corresponding author.
†These authors contributed equally.
giwoong.choi@uc.edu (G. W. Choi); sbae4@stevens.edu (S. W. Bae)
https://sites.google.com/view/giwoongchoi (G. W. Choi); https://www.stevens.edu/profile/sbae4 (S. W. Bae)
0000-0002-9631-3727 (G. W. Choi); 0000-0002-2047-1358 (S. W. Bae)

[5], reasoning [6], and communication [7]. One of the ways to foster metacognition among learners is to support their computational thinking process. Both computational thinking and metacognition emphasize problem solving. In fact, Yadav et al. [8] posits that computational thinking not only helps students become more familiar with computer science concepts but also promotes the development of metacognitive skills. Given that problem-solving is regarded as one of the most critical 21st-century skills [9], fostering these interconnected cognitive processes is essential for preparing learners for future real world challenges.

With this logical connection established between existing gaps and educational goals, we propose the MetaCoXAI framework, which links these three concepts both theoretically and practically. First, drawing from theoretical insights proposed by Yadav et al. [8], we reinforce the connection between metacognition and computational thinking and illustrate how the MetaCoXAI framework can enhance computational thinking, which in turn facilitates metacognitive development. Second, we identify specific XAI methodologies aligned with the phases of CT and provide practical examples of their application in educational contexts.

Our overarching research questions are as follows: **"How can theories of computational thinking and metacognition and explainable artificial intelligence be integrated to support learners?"** Our main contributions are twofold: (1) MetaCoXAI can assist researchers and developers in designing and evaluating new XAI systems that support the four phases of CT—*abstraction, decomposition, algorithm design, and debugging*—and (2) it enables educators to help students build metacognitive skills through XAI-enhanced learning environments, offering implications for educational researchers.

2. Related Works

2.1. Computational Thinking and Metacognition

This paper focuses on facilitating computational thinking (CT) skills and establishing a connection between CT and the theoretical concepts of metacognition. CT has gained significant attention among educational researchers as one of the key skills for the 21st century [10, 11]. While initially conceptualized as a skill specific to computer scientists, CT's problem-solving focus can be applicable to all learners. CT can be defined as the act of "solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science" [12].

The key concept closely related to CT is metacognition, which simply refers to "thinking about thinking" [13]. Martinez [14] expands on this, describing metacognition as "the monitoring and control of thought". Metacognition has been a critical component in self-regulated learning as metacognitive skills and knowledge play a crucial role in learners managing their own learning. The benefits of metacognition include "advancement in intellectual and academic growth, learning management, and complex problem-solving" [14]. Metacognitive practice consists of managing different skill sets used for problem solving, and involves scheduling, monitoring, and organizing skill use [15].

In the context of CT, metacognition occurs when learners reflect on their computational methods to solve human problems. In fact, metacognitive practices are considered to be one of the key evaluation approaches to CT [16]. The process of CT and metacognition can work in parallel [8]. By considering the four steps of CT—abstraction, decomposition, algorithms, and debugging — Yadav et al. [8] establish clear connections to metacognition. Abstraction involves identifying the problem and its parameters. Decomposition entails analyzing and breaking down problems into smaller parts. Algorithms involve devising step-by-step plans for solutions. Debugging includes evaluating and refining solutions. Together, these CT processes reflect metacognitive awareness and control in solving complex problems.

2.2. Computational Thinking and Metacognition, and Explainable AI

The fundamental idea behind XAI aligns with the explanatory aspect of CT, as its goal is to "enable end users to understand, trust, and effectively manage their intelligent partners" [17]. We propose that XAI can serve as a powerful computational tool that provides algorithmic explanations, fostering a

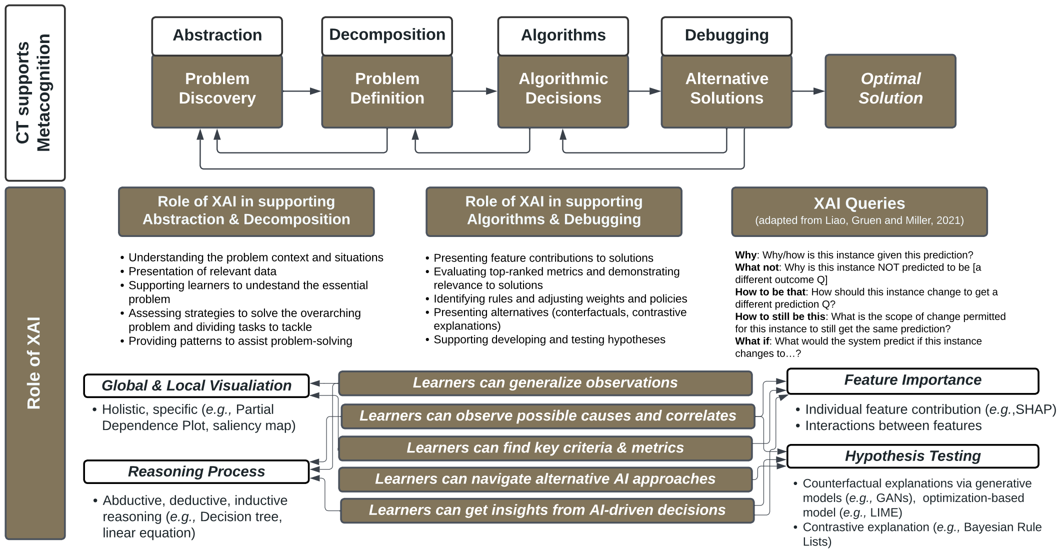

Figure 1: Overview of Our Proposed MetaCoXAI Framework

deeper comprehension of computational concepts and demonstrating algorithmic thinking. Therefore, we suggest that among the various approaches to CT, focusing on metacognition can assist learners through the utilization of XAI methods. According to Miller et al. [18], explainers wanted to generate explanations to allow explainees to learn either through the simplification of observed examples [19] or through the generalization of such observations that allow people to predict future events [20]. While transparency in presenting the algorithmic decision-making process is one of the key benefits of XAI methods, making the outputs generated by AI more understandable and interpretable can support learners in better understanding complex problems and help learners develop stronger computational thinking skills. In the next section, we present how XAI can assist learners in facilitating computational thinking (CT) skills, encompassing the four steps of abstraction, decomposition, algorithms, and debugging, as proposed by Yadav et al. [8], in conjunction with metacognition.

3. MetaCoXAI Framework: "How Explainable AI Supports Computational Thinking Process?

Our MetaCoXAI framework primarily focuses on designing and developing XAI for learning purposes and holds significant educational implications. In fact, the notion of explainability in XAI aligns with the concept of CT, and this brings forth possibilities of utilizing XAI as an instructional instrument for CT. Because of XAI's explainability, learners will be able to understand how AI algorithmic functions work [21], which could potentially benefit learners to utilize AI systems to solve problems using CT skills. Recently, there have been discussions on how XAI can support learning. Khosravi et al. [22] list "agency, student-teacher interactions, AI literacy, accountability and trust" as the main benefits of XAI in education. In our model, we focus on XAI's capacity to facilitate computational thinking and metacognition. We posit that XAI supports computational thinking process and metacognitive activities in relation to problem solving. With this in mind, Figure 1 illustrates how the MetaCoXAI framework supports each process of CT (abstract, decomposition, algorithms, and debugging), which is closely associated with metacognition. First, building upon the work of Yadav et al.'s [8], we demonstrate how metacognition and CT are linked to each other in terms of problem-solving. Subsequently, we provide visualizations to illustrate how XAI capabilities can support the processes of CT. We categorize XAI functionalities into four groups to demonstrate their relevance to learners' CT processes. The framework also demonstrates how XA functionalities (e.g. Global/Local Visualization; Reasoning Process; Feature

Importance; and Hypothesis Testing) involve XA queries that can enable learners to conduct problem solving activities using computations. In the next section, we provide a conceptual framework that demonstrates how the potential benefits of XAI methods and techniques can be leveraged to support the four processes of CT within learning contexts.

3.1. Role of XAI in Supporting Abstraction and Decomposition

3.1.1. How XAI Supports Abstraction

Problem solving becomes evident when students learn new topics and reflect on them in the classroom; however, setting a good problem for students to solve independently poses a challenge when they lack the necessary knowledge, specific information, and relevant data. While abstraction is defined as a metacognitive process of identifying the problem and its parameters [8], the role of XAI in supporting this process within the learning context remains unknown. In the field of HCI, Wang et al. [17], introduced how AI techniques generate explanations at various levels to design user-centric XAI, supporting human perception, reasoning processing, and mitigating heuristic biases. They leverage different types of XAI facilities such as Bayesian probability, similarity modeling, intelligibility queries, explanation elements, data structures, and visualization. Moreover, Liao et al. [23] proposed a set of queries that different XAI algorithms can trigger.

As such, by presenting "how algorithms work" with the assistance of XAI, students can explore data (input factor) more transparently, and it helps them to attain relevant data samples related to the specific topics they are learning and understand how each data point contributes to the targeted variable (output factor). XAI can help learners understand AI better by displaying how each AI function works and understand the given problem through the lens of AI. XAI facilitates their knowledge discovery process. By exploring data and understanding how AI works and why it makes certain decisions, students are empowered to generate new and novel questions that they have not previously explored.

3.1.2. How XAI Supports Decomposition

Decomposition is the process of breaking down a large problem into sub-problems (e.g. at the task level). XAI offers users the ability to explore data at both the global and local levels of model generation. Specifically, through the use of XAI's Local Interpretable Model Explanations, students can examine how a particular example could be related to the targeted predictive value or problem. This allows learners to uncover interesting trends and relevant features concerning the issue of the subject matter and raises awareness of how data samples are associated with the problem.

Within the realm of XAI, learners can benefit from gaining holistic perspectives on data exploration. Global agnostic models play a crucial role in facilitating data exploration, as they allow learners to develop a comprehensive understanding of the decision-making process employed by AI systems. By leveraging techniques such as feature influence and relevance, learners can effectively grasp the rationale behind AI-generated decisions. The utilization of global models provides learners with a broader understanding of data and patterns, enabling them to identify high-level problems with greater clarity.

Given the abundance of information and data looking for goals to achieve, it is essential to identify both the positive factors that contribute to achieving goals and the obstacles that hinder them. Global explanations amongst XAI techniques aim to describe how the entire machine learning model operates and assist learners in understanding how each factor influences the output. Global explanations provide insights into the relationship between each feature and predictions [22].

Amongst the different XAI strategies, one commonly used approach is Shapley Additive exPlanations (SHAP), which utilizes Shapley values derived from game theory [24, 25, 26]. SHAP allows learners to understand the key contributors and the direction (positive or negative) of their impact on the machine learning model. It provides a baseline of the model by presenting the mean predictive value, and presents how far or close each feature is from the base data point and identifies deviation from the average value (baseline). For this reason, learners can interpret the contribution of each feature.

3.2. Role of XAI in Supporting Algorithms and Debugging

3.2.1. How XAI Supports Algorithms

According to Yadav et al., [8], algorithms refer to the process by which learners justify the required steps to solve a problem. To make plans for a step-by-step execution to solve the problem, understanding different algorithmic decision-making would help learners practice how those strategies generate different results. XAI can facilitate problem solving and reasoning processes and give an understanding of how data is used, and justify actions derived from the output of machine learning models, ensuring its incorporation with data. First, XAI can support visualization techniques that aid in understanding why an algorithm produces specific outputs. Second, example-based explanation such as prototypes and graphs, offer new ways to analyze data and trigger human reasoning process. Learners may value the mental model of AI and its decision-making if a proper design is provided. However, in learning settings, it is important to use interpretable feature names that are simple enough for learners to understand how rules are created via AI. XAI supports the algorithmic process by allowing learners to explore specifics and analyze features interactions. Local models, such as Local Rule-Based Explanations (LORE) and Local Interpretable Model-agnostic Explanations (LIME) [27], provide instance-level models instead of using the entire dataset commonly used by global models. These local models demonstrate interactions between input features and their contributions, which can change the values of predictive models accordingly. By employing local models, learners can identify the input features that, if slightly altered, could result in different outcomes. This helps learners dissect complex problems and generate better ideas before planning and executing the necessary steps.

Importantly, XAI supports the algorithmic process by helping learners approach different aspects and approaches to finding solutions. While AI is often considered a black-box model, XAI reveals the specific steps algorithms take to execute a model. Learners have the opportunity to observe how algorithms solve problems. For example, rule-based models like decision trees and regression demonstrate how algorithms generate logic and rules using the given data to produce expected outputs. Learners can gain insights into the reasoning behind algorithmic decisions, even if some decisions may seem counterintuitive. XAI makes algorithmic decisions more interpretable, allowing learners to understand how and why such decisions are made. In addition, instance or example-based understanding, with the use of XAI visualization, helps learners explore different aspects of AI-generated decision in a transparent way.

3.2.2. How XAI Supports Debugging

Debugging is defined as finding the best solution and exploring alternatives, where learners evaluate the current solution and navigate possible alternatives to maximize the output. The next step is to assess the reliability of the predictive value (output) and find a way to optimize the model. Understanding the contribution of each factor in the data on the prediction produced by Feature Attribution and Importance of XAI as shown in [25, 27], is critical because learners can test different algorithms, data, and parameters by evaluating both individual level of features (weight) and identifying the top-ranked set of features to optimize the model. At the same time, learners can exclude irrelevant data that might negatively impact the predictive value, therefore maximizing the effectiveness of the model.

Nevertheless, not all XAI approaches are intuitive and valuable to learners, especially those without prior programming experience, due to the high AI literacy required. XAI strategies should be well-aligned with clear learning purposes and expected learner outcomes. Aside from that, XAI strategies can be beneficial for learners to explore data, analyze and define problems, facilitate understanding and reasoning process, and generate possible solutions. They also support the evaluation and debugging of output performance.

XAI supports debugging by assisting learners in finding alternative solutions. For example, counterfactuals explanations [28] enable learners to experiment with algorithm-generated hypothesis testing which provides possible conditions of feature combinations that affect predictions (e.g., different counterfactual outputs of Counterfactual Explainer). Learners can discover alternatives they had not previously considered but recognize hypothetical adjustments to specific input factors that could change the algorithm's output, for example, from a positive to a negative influence. Such methods empower students to create alternative solutions. By looking at contrastive explanations, students can learn how to come up with alternative solutions by observing how AI determines which input factors produce contrastive examples. It demonstrates why something plausible did not occur by comparing it to why it did happen. Certain XAI approaches can facilitate hypothesis testing, where students explore different data or types of algorithms to see how these changes yield new findings (what-if explanation). This process can provide students with alternatives that may be superior to the current solution.

4. Research Implications and Future Directions

The proposed MetaCoXAI framework contributes to the theoretical understanding and practical implementation of XAI within CT to enhance metacognitive skills among learners. However, while the theoretical relationships outlined here establish a foundational perspective, their empirical validation is essential to substantiate and refine these conceptual connections. Several promising future research directions emerge from this work. First, integrating generative AI, particularly advanced large language models such as GPT-4o [2], offers substantial potential to enhance the framework by providing learners with interactive, dialogue-driven AI experiences. Recent studies [29] suggest that generative AI facilitates deeper cognitive and metacognitive engagement, promoting reflective learning experiences through interactive dialogues and real-time explanatory feedback [30]. Investigating the specific ways generative AI support computational thinking remains a critical area for empirical inquiry.

Second, the development of personalized and adaptive learning environments leveraging XAI present another valuable direction. Research by Holstein et al. [31] demonstrates that adaptive educational environments effectively support individual learners' cognitive and metacognitive skills, dynamically adjusting instructional methods based on real-time learner feedback and data-driven insights. Future research should explore how XAI specifically facilitates the scaffolding of metacognitive skills within adaptive computational thinking tasks.

Third, using XAI to enhance AI literacy and ethical decision-making aligns directly with critical metacognitive skills, particularly critical reflection and evaluative judgment. According to recent findings by Tankelevitch et al. [32], explicit, transparent explanations of AI-driven decisions significantly enrich learners' understanding of algorithmic processes, thereby reinforcing ethical reasoning and metacognitive awareness. Khosravi et al.[22] suggest that transparent AI systems that clearly communicate the reasoning behind algorithmic decisions not only enhance learners' understanding but also promote ethical and critical reflection. This alignment reinforces the educational value of the MetaCoXAI framework by integrating moral reasoning within computational thinking processes. Future studies should empirically assess the MetaCoXAI framework's effectiveness in fostering such ethical and reflective competencies.

Fourth, leveraging advanced learning analytics with XAI for systematic assessment of computational thinking and metacognitive processes could substantially improve educational interventions. Matcha et al. [33] highlight that analytics-driven feedback can facilitate timely instructional adjustments. Empirical exploration of these analytics approaches within the MetaCoXAI framework will clarify their practical impact on learner outcomes.

Last, ensuring educator preparedness through targeted professional development programs is vital for the successful integration of XAI in classrooms. Future work should focus on developing, implementing, and evaluating teacher training modules that specifically address educators' skills and attitudes towards XAI, as proposed by Vuorikari et al. [34]. This would enable broader adoption and deeper understanding of computational thinking pedagogies supported by XAI. There are a few limitations. First, since this is a preliminary work that focuses on a conceptual framework, future studies need to empirically test the the framework in educational settings. Second, the theoretical framework aims to provide general overview of the relationships between XAI, computational thinking, and metacognition and is not tailored to various learning contexts or learner characteristics. Hence, it would be important to focus on specific use cases in future studies.

5. Conclusion

While previous research has explored the advantages of XAI in learning and human decision-making domains, limited understanding exists regarding how XAI can effectively facilitate the process of CT in conjunction with metacognition. This paper aims to present a conceptual framework, called MetaCoXAI, that elucidates the intricate relationship between XAI, CT, and metacognition. First, we conduct a comprehensive review to analyze the interconnectedness between computational thinking and metacognition. Second, we argue that the integration of XAI, CT, and metacognition exemplifies a human-centered design approach to artificial intelligence and educational practices. Guided by this perspective, we introduce MetaCoXAI, a framework that provides detailed insights into how XAI can effectively foster and enhance CT. Our study introduces the MetaCoXAI framework, which is founded upon a robust theoretical foundation that aligns the various components of XAI with the goal of supporting CT. Specifically, we assert that XAI has the potential to facilitate metacognitive practice among learners, thereby enhancing the CT process and ultimately leading to improved performance and productivity in learning contexts. Our contribution lies in providing a comprehensive explication of how the components of XAI can be interconnected with the four fundamental concepts of CT from the learners' perspective: abstraction, decomposition, algorithm, and debugging.

Declaration on Generative AI

The author has not employed any Generative AI tools.

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