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Preliminary Study on the Study of Cognitive Science through the Construction of Problem-Solving Models to Promote AI Literacy

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Abstract: Recent educational research has highlighted the necessity of AI literacy. To use AI effectively in problem-solving, it is important to understand the nature of human intelligence in it as well. As a first step to develop its learning framework, this study designed learning materials and an activity for students not majoring in information science. Students studied problem solving through the construction of production-system models with instructional texts. While most students could not successfully construct all models, we confirmed that model construction can foster students' awareness of the nature of human thought.

Keywords: AI literacy, problem solving, learning by modeling, production system

1. Introduction

As AI technology has rapidly progressed and spread, educational research has highlighted the necessity of AI literacy (Almatraf, Johri, & Lee, 2023; Long, & Magerko, 2020) in modern society. Several attempts to promote AI literacy have been made to enable students to understand AI and its effective and ethical use. While definitions of constructs of AI literacy vary across researchers (Almatraf et al., 2023), many frameworks incorporate common elements, including recognition of AI's existence, understanding of AI principles, skills for using AI and evaluating its output, and ethical considerations in AI.

To effectively use AI in problem-solving, it is important to understand the nature of human intelligence in it. Pinski and Benlian (2023) proposed AI literacy, including understanding the roles of both humans and AI in human–AI collaboration and interaction, as AI artifacts are autonomous, aware of their environment, functionally inconsistent, and not transparent, while conventional information systems are used by humans to obtain consistent outcomes from defined inputs. Long and Magerko (2020) included a competency for analyzing and discussing features and differences among human, animal, and machine intelligence in AI literacy. Therefore, it is effective to improve the understanding of human intelligence to promote one aspect of AI literacy as problem-solving competencies. For this, approaches exploring human intelligence in cognitive science would be promising but also difficult for novice learners.

The final goal of this study is to develop a learning framework to study the nature of human intelligence in problem solving. This framework adopts the construction of computational models that have been used in cognitive science research as a learning activity. As a first step, the current study designed learning materials and an activity for novice students. While model construction is useful in studying invisible targets, it remains an intensive and challenging task requiring advanced computing skills. Thus, we preliminarily confirmed the model construction by students not majoring in information science.

2. Learning through the Construction of Problem-Solving Models

2.1 Learning by modeling

Cognitive science emerged simultaneously with AI from the 1956 Dartmouth workshop. In addition to building an intelligent machine, AI's main goals involve discovering the nature of intelligence (Schank, 1987). Cognitive science research has employed empirical studies of human behavior and computational models to understand the human mind (Schunn, Crowley, & Okada, 1998).

In addition to science research, science education uses models to allow learners to interpret scientific knowledge. Beyond model use, the construction and simulation of models by learners have also been examined (e.g., Clement, 2000; Gilbert, 2004). While model construction is generally challenging, requiring extensive skills training, it is promising for examining invisible targets such as cognitive processes. This modeling can make hidden assumptions explicit and activate reflective thinking or meta-monitoring in cognitive processes (Fum, Del Missier, & Stocco, 2007; Miwa, Morita, Nakaike, & Terai, 2014).

We developed a learning framework in which undergraduate students create models in a production system for novices, called DoCoPro (Nakaike, Miwa, Morita, & Terai, 2009). We conducted practices in university cognitive science classes and confirmed the learning effects of model construction (e.g., Saito, Miwa, Kanzaki, Terai, Kojima, Nakaike, & Morita, 2013; Miwa, Kanzaki, Terai, Kojima, Nakaike, Morita, & Saito, 2015). However, some students in the classes failed to construct successful models and did not gain sufficient learning effects, although they majored in informatics.

2.2 Learning environment and materials used in this study

This study used DoCoPro as the learning environment. To allow novices to experience model construction, DoCoPro limits constructs. Students only need to learn about if-then rules, working memory, matching, and built-in functions (e.g., functions to test whether two values are equal and to add an assertion to the working memory). DoCoPro includes no function to resolve conflicts among rules; if multiple rules are triggered at one step, the first rule in the array fires. It also has no functions to efficiently perform simulation or to represent human cognitive functions for scientific research. Instead, it helps students examine rules through trial and error providing functions to test these rules in a variety of ways.

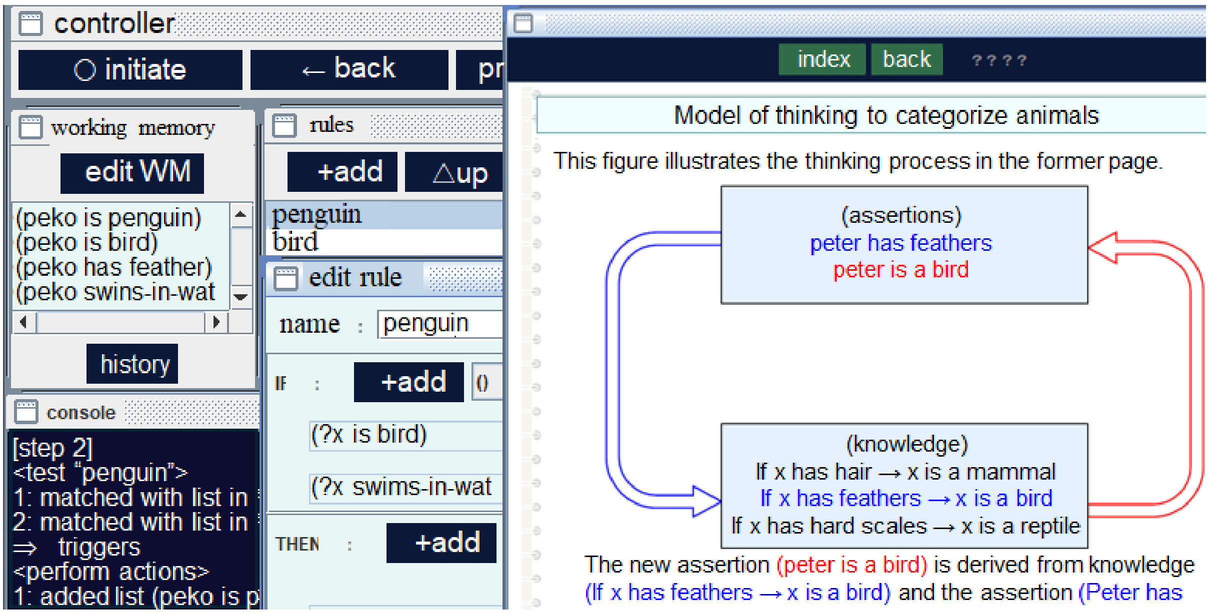


Figure 1. Part of a screenshot of DoCoPro.

Figure 1 shows a screenshot of DoCoPro, in which a student has constructed a model by inputting the initial state of a problem in the left working-memory frame, editing if-then rules in the middle frame, and simulating problem-solving by executing the model with the controller in the upper frame.

DoCoPro can present HTML documents as instructional texts in the right frame of Figure 1. Each document can include code in a CDATA Section, enabling DoCoPro to perform such actions as setting specific values in the working memory or adding an incomplete rule to the rules frame. This function of the instructional texts allows DoCoPro to guide novices in experiencing model construction.

While DoCoPro is a simple tool that has limited constructs, it can still be difficult for novice students who have not trained computing skills. Therefore, it was enhanced to allow the editing of states in the working memory and conditions and actions in the rules by creating and arranging blocks of values and variables. Figure 2 demonstrates the editing of an action in a rule. This helps novices create models using consistent problem descriptions. They occasionally fail to create an executable model because they use inconsistent descriptions between the working memory and rules.

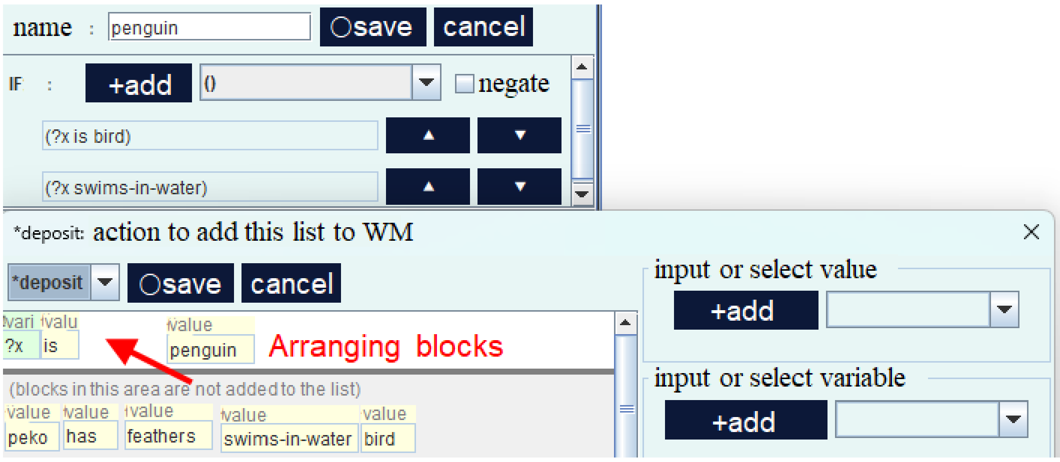


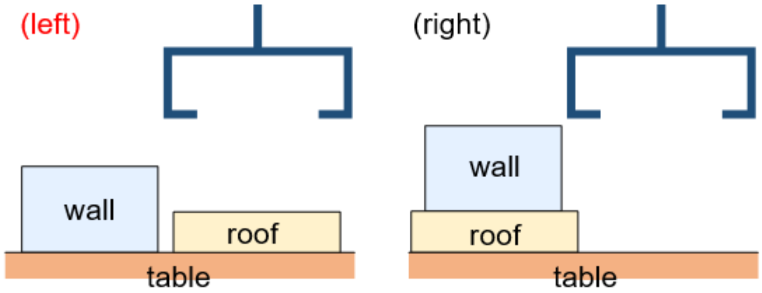
Figure 2. Edit of an action in a rule by arranging blocks.

This study also designed learning materials to guide the experience of model construction by novice students, as provided in the instructional-texts frame. The text consists of four chapters. The first explains if-then rules and reasoning using the example of animal classification like the zookeeper in Winston (1985). Using a working memory and an if-then rule, students learn to model a thought to lead to the new assertion “an animal is a bird” from the knowledge “if *x* has feathers, then *x* is a bird” and the assertion “the animal has feathers.” They also create the rule “if x is a bird, and *x* swims in water, then *x* is a penguin” and learn chaining reasoning using the two rules. The two rules are provided from the texts, and students merely input them.

In the second chapter, students learn a framework to model problem-solving through the example of traveling to school. They are first introduced to the framework “reaching a goal state from an initial state through state transitions by applying operators” and are then instructed to describe states in working memory and to implement operators with rules. They input the initial state (at Suzumenomiya-station[1]) and the *move-by-train* rule “if at Suzumenomiya-station, then delete (at Suzumenomiya-station) and add (at Utsunomiya-station[1]).” They create the next *move-by-bus* rule to travel to the university from Utsunomiya Station on their own. The final rule to finish the problem-solving process when reaching the goal state is provided. Students reproduce the entire process from Suzumenomiya Station to the university via Utsunomiya Station by train and bus.

[1] Suzumenomiya and Utsunomiya Stations are located near the first author’s university. Many students use these stations.

The third chapter shows a more complex model, building blocks. Figure 3 gives part of the third chapter. While it only requires stacking a roof block on a wall block, each rule of the model must delete and add multiple state descriptions. This model includes five rules. Students are given two of these, create the other two according to rules described in natural language, and create the final rule on their own.



To reach the goal state, you pick the roof and put it on the wall. This works well in the left state; however, you must first pick up the wall because you cannot pick up the roof.

Create the operation to pick up a block for the left state. It is U-R rule because the target is the roof.

IF
- the roof is on the table
- no block is on the roof
- the crane holds nothing

THEN
- hold the roof with the crane
  - or a state "the crane holds the roof" is now true
  - a state "the roof is on the table" is no longer true

Figure 3. Part of the third chapter of the instructional texts.

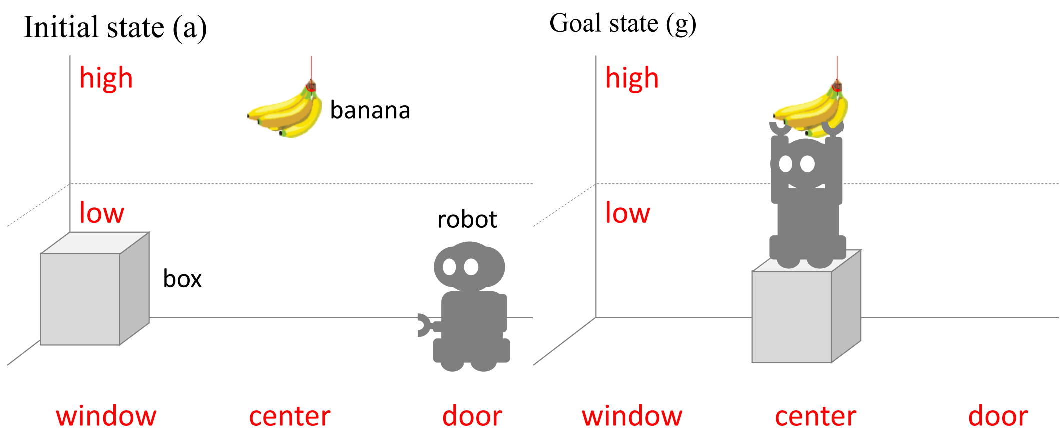


Figure 4. Initial and goal states in the robot and banana problem.

The final chapter presents the robot and banana problem, an altered version of the famous toy problem of the monkey and the banana. Its initial and goal states are illustrated in Figure 4. In this problem, the robot is to carry the box to the center of the room and retrieves the banana by standing on the box. This chapter provides four rules, described in natural language. Students design descriptions to represent the initial state in the working memory, create the four rules with descriptions, and create a final rule on their own.

The building blocks and the robot and banana problem are simple. Nevertheless, their modeling is more difficult than logical thinking using domain knowledge, as in the first chapter. Thus, these materials are expected to foster students' awareness of thinking that is easy or difficult for humans.

3. Empirical Study

3.1 Method

We empirically assessed whether novice students successfully constructed models with DoCoPro and the materials previously described. In all, 10 undergraduate students in the department of economics participated in lectures on model construction as part of an information literacy course. They learned basic computer operations, use of office suite software, and composition of documents and slides to present their own ideas in the course.

Three lectures on model construction were provided. In the first, the students received an explanation of the summary and purpose of the model construction lectures. They then learned model construction according to the first to third chapters of the instructional texts of DoCoPro. They were instructed to complete the three chapters before the next lecture. In the second lecture, they worked on model construction of the robot and banana problem, following the fourth chapter.

Finally, for the third lecture, the students were given two worksheets. One presented a new problem, and they described its initial and goal states as well as if-then rules that could solve the problem. In the other worksheet, students answered three questions: why is model construction so difficult, where does humans thought excel, and what did you learn in the model construction? The analytical results of the worksheets are omitted here due to the page limitation.

3.2 Data analysis

We checked whether the students successfully completed the robot and banana model problem. Their models were divided into the following three categories.

- *failed* models did not function at all.
- *incomplete* models only reproduced part of the robot and banana problem.
- *complete* models entirely reproduced the problem.

We also added labels representing the cause of the failure for each failed/incomplete model.

- *inconsistent* models used descriptions that differed between working memory and rules, which must have been the same.
- *misspelling* used descriptions identical between working memory and rules, but the misspelling of a word prevented model functioning.
- *inappropriate conditions* prevented the right rule from triggering or caused a wrong rule to trigger due to incomplete conditions.
- *missing rules* did not create all five rules.

3.3 Results and discussion

We analyzed the data of seven out of the ten students who attended all three lectures and submitted all four models. Their models of the first to the third chapters were all complete. Among their models of the robot and banana problem, two were complete and five were incomplete. Figure 5 indicates the numbers of the failed and incomplete models that were added to each label of causes of failure. All five models had inappropriate conditions. As explained in Section 3.1, four of the five rules necessary to complete were given in natural language sentences, and each rule clearly presented two to four conditions. However, two students described fewer conditions in each rule for unclear reasons. They may have misunderstood the instruction, or there may have been other difficulties for novices in model construction.

As described earlier, the current study preliminarily investigated the model construction by novice students. In this respect, the enhancement of support for model construction is necessary.

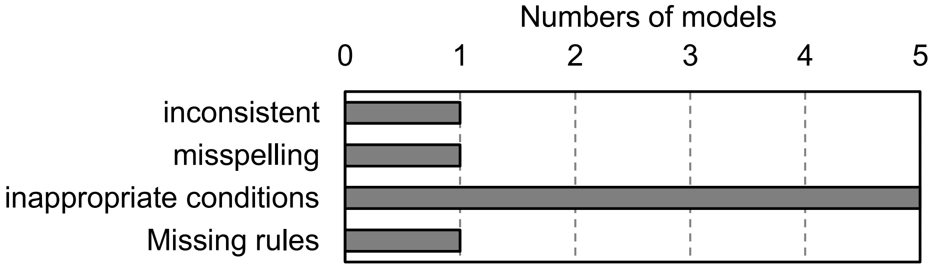


Figure 5. Numbers of the failed and incomplete models that were added to each cause-failure label.

In the second worksheet, students' answers included certain important concepts, such as *ambiguous* and *indefinite* for human strength, and *unconscious* and *difficult to externalize thought* for learning from model construction. While this study had only small samples, it may insist the possibility that model construction can foster awareness of the nature of human thought, which can lead to the understanding of the nature of human intelligence in problem solving. Of course, further investigation to verify the learning effects is necessary. Another important future work is to design further materials to expand what students learn about human intelligence.

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