# Fostering Effective Interaction with Intelligent Pedagogical Agents to Help Children learn Computational Thinking Skills

Cristina Conati
Dept. of Computer Science, University of British Columbia

Sébastien Lalle,
Dept. of Computer Science, Sorbonne University

Nilay Yalcin,
School of Interactive Arts, Simon Fraser University

**Abstract.** Research suggests AI-driven personalized support can help students learn from Open-Ended Learning Environments (OELEs). We are specifically looking at Pedagogical Agents that provide AI-driven personalized support in a OELE designed to foster computational thinking skills via free-form game design in K-6 education. However,
delivering such support in an effective and unobtrusive manner can be challenging, especially with younger students. We have thus far addressed issues such as how to effectively provide repeated hints, namely help when students repeat a suboptimal behavior (e.g., an error) after receiving a hint on how to recover from the first occurrence of the behavior. However, we have not done any speech or NLP processing yet, all our dialogues have been based on canned text. We are now interested in exploring how speech and NLP could help with devising pedagogical dialogues that foster learning and motivation in our young audience

**Keywords:** Open-Ended Learning Environment, Real-Time Support, Hint Design, Pedagogical Agents

## 1 Introduction

There is mounting evidence that AI-driven personalized support can help stu- dents learn from Open-Ended Learning Environments (OELEs), namely edu- cational software that is specifically designed to let the students learn via ex- ploration of the learning material with minimal constraints [13, 15, 20, 23, 24, 28]. However, delivering such help in a way that is effective and well accepted by students is difficult, due to two main challenges. The first challenge relates to *student modeling*, namely, how to capture and recognize students' behaviors that indicate the need for help. The second challenge relates to *how to deliver the help effectively*, without being too intrusive nor interfering with the exploratory nature of the interaction with the OELE [1, 26].

The long-term goal of our research is to study how to design effective per- sonalized help in the context of OELEs that support game-based activities for elementary school students. This context is especially challenging from the point of view of delivering help that is effective and not intrusive, because younger stu- dents tend to become highly engaged in game-based activities and thus are more prone to perceive offers of help as undesirable interruptions that interfere with their flow and reduce their motivation [10, 22, 14]. For this purpose, we leverage

Unity-CT, an OELE designed and commercialized by a UME, a local company, to foster computational thinking (CT) skills in K-6 education. With this OELE, students can engage in free-form game-based activities, where they create and play video games following a curriculum designed to incremen- tally introduce various CT skills.

The student modeling challenge of delivering personalized help in Unity-CT has been addressed in [17], by applying a data-driven framework for user mod- eling and adaptation (FUMA, [15]) to Unity-CT. This work showed that FUMA could infer from data a variety of nonobvious suboptimal student behaviors that call for personalized help. In parallel, we address the challenge of *how to de- liver this personalized help effectively* once the need for it has been established by the student model.

## 2 Delivering Effective AI-Drive Help in Unity-CT

In recent years, there has been increasing interest in fostering CT in K- 12 education [2]. Unity-CT, which is built on the Unity game engine, was developed to engage elementary school students with CT by leveraging free-form game design activities. It consists of a curriculum of 8 lessons to introduce the CT skills as suitable for young audiences. These skills are di- vided into higher-level problem-solving practices that emerge during algorithmic and programming processes, and lower-level programming concepts employed for coding. The online version of the curriculum that has been used since November 2020 to deliver 800+ classes in North America. During each lesson, lasting 1 hour, an instructor demonstrates a set of game- design functionalities targeting the CT skills covered in that lesson, and then assigns a 30-minute challenge to design incremental game components that meet specific constraints. Students can freely explore how to build these components via an interactive scene view in which they can manipulate game objects. Different manipulators allow different interactions with the objects in the scene (e.g., move, resize and rotate).

Results from evaluations of Unity-CT are in line with research showing that game-based activities increase student engagement in CT classes [4, 9], however, Unity-CT introduces specific challenges due to students having to both operate in the complex Unity interface and learn the CT material. Although students can ask the instructor for help, not all students do it. Instructors generally try to watch for students needing help, but this is challenging without continuously monitoring what each student is doing on their computer. Thus, we are collaborating with UME to augment Unity-CT with *Intelligent Pedagogical Agents* (*IPA* from now on) that can deliver personalized help when a student needs it. A main challenge of this endeavor is how to make sure that children pay attention and follow the help, making sure that the help does not interfere with student's engagement and motivation.

For instance, we have been investigating how to effectively deliver a specific form of help, namely how to effectively provide *repeated hints* when students repeat sub-optimal behaviors and they have already received a hint on how to recover from the first occurrence of the behavior. We focused on hint repetition because this is one aspect of supporting effective learning with OELEs where it is crucial to understand how to provide sufficient guidance without being too intrusive and interfering with the exploratory nature of OELEs [19, 6].

Most previous research on this issue [15, 6, 7] targeted university students and OELEs that do not include game-based activities, thus their find- ings may not generalize to younger K-6 students engaged with OELEs that are game-based.

As a first step to investigate how to provide effective repeated hints in Unity-CT, we focused on two well-defined errors that students frequently make in using the Unity-CT interface [31]. We compared the effectiveness of repeating a hint against providing it only once the first time one of these errors occurs. Hints here are delivered by the IPA via text in speech bubbles, as shown in Figure 1 and Figure 2 below. We found that, for one of these error types, repeating the hints helped students make fewer errors and perform more correct actions, however, they did not help the students correct their errors after they were made, in comparison to receiving the hints only once. Also, the repeated hints generated higher levels of student self-reported confusion, although they received very positive ratings for other usability measures (liking, helpfulness, distraction and intent to reuse).

We then built on these results to see if we can improve the design of these repeated hints to alleviate the issues of increased confusion and lack of impact on error correction. We did so by varying how the first hints and their repeated versions are delivered: namely while the first hint consists of different parts that the student can access in sequence (e.g. see Figure 1) in the repeated hint

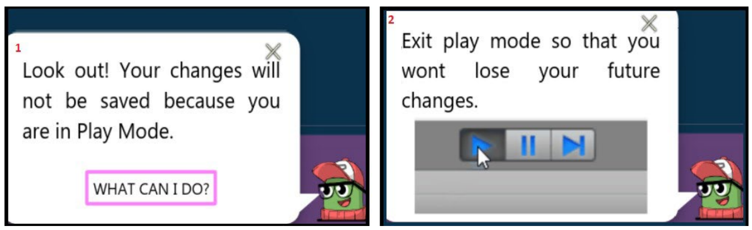


**Fig. 1.** First hint for the PlayMode error, delivered via two sequential speech bubbles. The image in the last bubble is an animated GIF.

all the parts are summarized in one single delivery (e.g. see Figure 2), based on the existing evidence that varying the repeated hints was successful in other contexts [15, 3, 6].

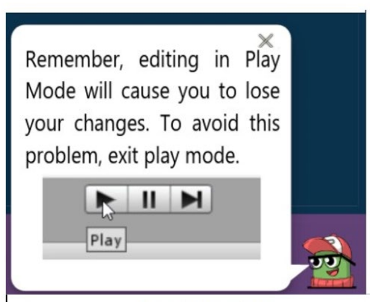


**Fig. 2.** Repeated hints with all text combined in one speech bubble for PlayMode

We then compare this design against not varying the delivery of the repeated hints, that is, repeating hints with the same sequential delivery as the first hint, as done in [31]. The evaluation of the new hints was conducted in fully ecological settings, during several of the in-line classes delivered with Unity-CT. Our results [32] show that the new design was successful in reducing student reported confusion with the hints, and in improving error correction for one of the two error types. The results also generated insights of why the new design did not help with the correction of the second error type, and how to address this limitation in the future

## 3 Future Work: Multimodal Pedagical Dialogue

Our findings so far provide a promising proof of concept for the value of adaptive interventions to support young learners in a game-based open-ended learning setting that is becoming increasingly used in K-6 education to foster CT, e.g., [30, 16]. However, these findings only scratch the surface of what is needed to provide effective AI-driven support in this challenging context. Isolating specific aspects of what makes OELE's personalized support effective in different contexts is crucial. We have uncovered design insights related to a specific aspect of how to deliver repeated hints on two well defined performance errors. However, these hints were delivered via simple canned text presented through speech bubbles (see Appendix), that students interact with via mouse clicks. One critical next step in this research will be to investigate the added value of extending this simple interaction into richer multimodal dialogue, leveraging both speech and NLP to investigate how to manage conversational flow and repair in the pedagogical interaction, which we see a key aspect to balance the need to provide didactic help and to maintain student engagement and motivation; The next step will then be to extend the pedagogical dialogue to cover a broader set of behaviors relevant to the Unity-CT curriculum, as they were uncovered by the Fuma student model [17].

## References


1. Aleven, V. Help seeking and intelligent tutoring systems: Theoretical perspectives and a step towards theoretical integration. In *International handbook of metacogni- tion and learning technologies*. Springer, New York, NY, USA, 2013, pp. 311–335.
2. Barr, V., and Stephenson, C. Bringing computational thinking to K-12: what is Involved and what is the role of the computer science education community? *Acm Inroads 2*, 1 (2011), 48–54. Publisher: ACM New York, NY, USA.
3. Basu, S., Biswas, G., and Kinnebrew, J. S. Learner modeling for adaptive scaffolding in a Computational Thinking-based science learning environment. *User Modeling and User-Adapted Interaction 27*, 1 (Mar. 2017), 5–53.
4. Biswas, G., Segedy, J. R., and Kinnebrew, J. S. Smart Open-Ended Learning Environments That Support Learners Cognitive and Metacognitive Processes. In *Human-Computer Interaction and Knowledge Discovery in Complex, Unstructured, Big Data* (Berlin, Heidelberg, 2013), A. Holzinger and G. Pasi, Eds., Lecture Notes in Computer Science, Springer, pp. 303–310.
5. Bolker, B. M., Brooks, M. E., Clark, C. J., Geange, S. W., Poulsen, J. R., Stevens, M. H. H., and White, J.-S. S. Generalized linear mixed models: apractical guide for ecology and evolution. *Trends in ecology & evolution 24*, 3 (2009), 127–135.
6. Borek, A., McLaren, B. M., Karabinos, M., and Yaron, D. How much assistance is helpful to students in discovery learning? In *Learning in the Synergy of Multiple Disciplines* (Berlin, Heidelberg, 2009), U. Cress, V. Dimitrova, and M. Specht, Eds., Springer Berlin Heidelberg, pp. 391–404.
7. Bouchet, F., Harley, J. M., and Azevedo, R. Impact of different pedagogical agents' adaptive self-regulated prompting strategies on learning with metatutor. In *International Conference on Artificial Intelligence in Education* (Memphis, TN, USA, 2013), Springer, pp. 815–819.
8. Cameron, A. C., and Trivedi, P. K. *Regression analysis of count data*, vol. 53. Cambridge university press, Cambridge, UK, 2013.
9. Çakır, N. A., Gass, A., Foster, A., and Lee, F. J. Development of a game- design workshop to promote young girls' interest towards computing through iden- tity exploration. *Computers & Education 108* (2017), 115–130. Publisher: Elsevier.
10. Charsky, D., and Ressler, W. "games are made for fun": Lessons on the effects of concept maps in the classroom use of computer games. *Computers & Education 56*, 3 (2011), 604–615.
11. Field, A., Miles, J., and Field, Z. *Discovering statistics using R*. Sage publi- cations, London, UK, 2012.
12. Fisher, R. A. On the interpretation of $\chi$ 2 from contingency tables, and the calculation of p. *Journal of the Royal Statistical Society 85*, 1 (1922), 87–94.
13. Grivokostopoulou, F., Kovas, K., and Perikos, I. The effectiveness of em- bodied pedagogical agents and their impact on students learning in virtual worlds. *Applied Sciences 10*, 5 (2020), 1739.
14. Hsieh, Y.-H., Lin, Y.-C., and Hou, H.-T. Exploring the role of flow experience, learning performance and potential behavior clusters in elementary students' game- based learning. *Interactive Learning Environments 24*, 1 (2016), 178–193.
15. Kardan, S., and Conati, C. A Framework for Capturing Distinguishing User Interaction Behaviors in Novel Interfaces. In *Proceddings of the 4th International Confernece on Educational Data Mining* (Eindhoven, The Netherlands, 2011), IEDMS, pp. 159–168.
16. Koh, K. H., Repenning, A., Nickerson, H., Endo, Y., and Motter, P. Will it stick? exploring the sustainability of computational thinking education through game design. In *Proceeding of the 44th ACM Technical Symposium on Computer Science Education* (New York, NY, USA, 2013), SIGCSE '13, Association for Com- puting Machinery, p. 597–602.
17. Lallé, S., Yalçın, Ö. N., and Conati, C. Combining data-driven models and

expert knowledge for personalized support to foster computational thinking skills. In *11th International Learning Analytics and Knowledge Conference* (Irvine, CA, USA, 2021), ACM, pp. 375–385.

18. Lund, A. M. Measuring usability with the use questionnaire12. *Usability interface 8*, 2 (2001), 3–6.
19. Mavrikis, M., Gutierrez-Santos, S., Geraniou, E., and Noss, R. Design re- quirements, student perception indicators and validation metrics for intelligent ex- ploratory learning environments. *Personal and ubiquitous computing 17*, 8 (2013), 1605–1620.
20. McCarthy, K. S., Watanabe, M., Dai, J., and McNamara, D. S. Personalized learning in iSTART: Past modifications and future design. *Journal of Research on Technology in Education 52*, 3 (2020), 301–321. Publisher: Taylor & Francis.
21. Mellor, D., and Moore, K. A. The use of likert scales with children. *Journal of pediatric psychology 39*, 3 (2014), 369–379.
22. Nolan, J., and McBride, M. Beyond gamification: reconceptualizing game- based learning in early childhood environments. *Information, Communication & Society 17*, 5 (2014), 594–608.
23. Poitras, E. G., and Lajoie, S. P. Developing an agent-based adaptive system for scaffolding self-regulated inquiry learning in history education. *Educational Technology Research and Development 62*, 3 (2014), 335–366.
24. Price, T. W., and Barnes, T. Position paper: Block-based programming should offer intelligent support for learners. In *Proceedings of the IEEE Blocks and Beyond Workshop* (Raleigh, NC, USA, 2017), IEEE, pp. 65–68.
25. Reynolds, L., and Johnson, R. Is a picture is worth a thousand words? cre- ating effective questionnaires with pictures. *Practical Assessment, Research, and Evaluation 16*, 1 (2011), 8.
26. Roll, I., Aleven, V., McLaren, B. M., and Koedinger, K. R. Improving students' help-seeking skills using metacognitive feedback in an intelligent tutoring system. *Learning and instruction 21*, 2 (2011), 267–280.
27. Rose, S. P., Habgood, M. P. J., and Jay, T. Designing a programming game to improve children's procedural abstraction skills in scratch. *Journal of Educational Computing Research 58*, 7 (2020), 1372–1411.
28. Rowe, J., Mott, B., McQuiggan, S., Robison, J., Lee, S., and Lester, J. Crystal island: A narrative-centered learning environment for eighth grade micro- biology. In *workshop on intelligent educational games at the 14th international conference on artificial intelligence in education* (Brighton, UK, 2009), Springer, pp. 11–20.
29. Schroeder, N. L., Adesope, O. O., and Gilbert, R. B. How effective are pedagogical agents for learning? a meta-analytic review. *Journal of Educational Computing Research 49*, 1 (2013), 1–39.
30. Wu, M. L., and Richards, K. Facilitating computational thinking through game design. In *Edutainment Technologies. Educational Games and Virtual Real- ity/Augmented Reality Applications* (Berlin, Heidelberg, 2011), M. Chang, W.-Y. Hwang, M.-P. Chen, and W. Müller, Eds., Springer Berlin Heidelberg, pp. 220–227.
31. Yalçin, Ö N., Lallé, S., and Conati, C. An intelligent pedagogical agent to foster computational thinking in open-ended game design activities. In *27th International Conference on Intelligent User Interfaces* (Helsinki, Finland, 2022), ACM, pp. 633–645.
32. Lallé, S, Yalçin,O. Oonati C. How to Repeat Hints: Improving the effectiveness of AI-driven Help in Open-Ended Learning Environments. Submitted to AIED 2023. International Conference of AI in Edication