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Empowering K-12 Students with Computational Creativity: Towards A Constructionist Computational Creativity Model

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Recent developments in Artificial Intelligence (AI) are not only transforming society but are also increasingly shaping educational contexts. While AI technologies offer new possibilities for rich learning experiences, there is growing consensus that students should not only use AI systems but also be able to understand and design them. Constructionist learning environments provide a promising foundation for this shift, enabling learners to engage hands-on with AI by constructing meaningful artifacts. One particularly suitable domain for this is Computational Creativity (CC), which focuses on systems that generate novel outputs using AI techniques. In this paper, we introduce the Constructionist Computational Creativity (CCC) model, which aims to integrate CC into K–12 education in a way that fosters both creative expression and AI competencies. The model was developed through a synthesis of CC theory and constructionist pedagogy and was refined through an exploratory study with pre-service Computer Science teachers. Findings from this study show that engaging learners in the development of creative AI systems supports a deeper understanding of AI concepts, enhances computational thinking, and promotes reflection on creativity across domains. The CCC model thus offers a structured approach to integrating AI education into creative learning processes.

Keywords and Phrases: K-12 education, CS teachers' education, Computational Creativity, Constructionism.

1 INTRODUCTION

Constructionism, as established by Papert (1980) and further developed by others (Kafai, 2017; Kahn, 2021), emphasizes the importance of learning through making personally meaningful artifacts. This perspective has long been shown to support the development of computational thinking (CT) and creativity, especially in contexts where learners use programming environments and digital tools to express ideas and solve problems (Kahn, 2021, Przybylla & Romeike 2012).

As AI continues to shape society and digital practices across domains, the demand for effective educational approaches that foster AI literacy from an early age has grown significantly (Touretzky, 2019, Michaeli et al., 2023b). This presents a timely need to apply constructionist learning approaches; as they offer learners the opportunity to explore complex ideas through creative, hands-on experiences (Kafai, 2005). To date, many AI education initiatives in K–12 settings have focused on the use of AI systems or on understanding their societal implications. However, fewer approaches enable learners to actively construct AI systems themselves. We argue that engaging students in the design and development of AI systems holds considerable potential, particularly when grounded in constructionist learning theory (Morales-Navarro & Kafai, 2023).

In light of this, we explore how constructionist learning approaches can be extended into the domain of Computational Creativity (CC), a subfield of AI concerned with the generation of novel and meaningful outputs by machines (Boden, 2004). From an educational standpoint, CC presents a unique opportunity: it allows learners to engage with foundational AI ideas through the lens of creativity. Designing systems that can generate creative artifacts; such as stories, images, music or culinary recipes not only cultivates a deeper understanding of AI concepts, but also aligns with students' personal interests and creative expression.

In this paper, we introduce the Constructionist Computational Creativity (CCC) model as a framework for integrating AI competencies and creative learning in K–12 education. Our approach aims to address the current lack of structured pedagogical models that support students in building their own creative AI systems. Through this process, students gain insight into AI methods such as machine learning and generative models, while also developing a deeper understanding of creativity as a computational process. We argue that creativity, in this context, is not merely an outcome, but a method of engaging with AI in ways that are both educationally rich and personally relevant.

2 RELATED WORK

Creativity is increasingly recognized as a fundamental educational goal and a crucial 21st-century skill (Pllana, 2019). It involves the ability to generate novel and valuable ideas, solutions, or artifacts, whether in the arts, sciences, or technology. In educational contexts, creativity is nurtured not only as a cognitive capacity but also through hands-on, expressive activities that emphasize design, composition, and reflection (Kakarla, 2024). This broad understanding of creativity positions it as both a mode of problem-solving and a form of personal expression, highlighting its value in various approaches to computing education.

Creativity has long been a core element of constructionist learning environments. Based on the ideas of Papert (1980), constructionism emphasizes learning through the creation of meaningful artifacts. This pedagogical approach has been widely applied in computing to support the development of computational thinking (Grover, 2013), technical skills (Maloney, 2010), and creative exploration through visual programming environments such as Scratch, Snap!, and Logo (Maloney, 2012). Activities, ranging from unplugged tasks to digital creations, have been shown to enhance student engagement, especially when they involve open-ended, learner-centered projects (Lindner et al., 2019). Moreover, computational thinking itself is increasingly viewed as a means of creative expression, particularly in areas such as digital storytelling, visual art, and music (Wing, 2006; Brennan, 2012).

In parallel, the field of CC has emerged within AI research, focusing on the development of systems capable of producing creative artifacts in domains such as music (Carnovalini, 2020), art, and language (Colton, 2014; Sadiku, 2019). Foundational frameworks by Wiggins (2006), Boden (2009), and Pérez y Pérez (2015) describe CC systems in terms of structured search spaces, evaluation mechanisms, and reflective processes. While originally situated within theoretical AI research, CC is increasingly seen as a promising instrument for engaging students with AI concepts in an intuitive and motivating way (Artut, 2017; Peteranetz, 2019). Educational implementations of CC allow learners to experiment with creative algorithms, and explore how machines generate outputs (Peteranetz, 2019; Zhaochen, 2017). These CC-based activities align well with constructionist principles by supporting students as designers and experimenters. Rather than merely interacting with AI tools, learners engage in building their own creative AI systems; that generate stories, images, or musical compositions. This approach fosters deeper conceptual understanding of AI, including model design, data representation, and evaluation mechanisms, while simultaneously cultivating creative confidence (Peppler, 2005; Kafai, 2012).

Despite the growing interest in constructionist approaches to teaching both computational thinking and AI, and the promising potential of CC in educational settings, there remains a lack of structured pedagogical frameworks to support educators in implementing these ideas. Current efforts tend to emphasize co-creation with AI or integrate creativity through programming tasks, but few provide guidance on how students can become builders of AI-based CC systems. This gap highlights the need for a framework that connects core CC system components with constructionist learning practices to foster student agency, creativity, and AI literacy. In this paper, we address this gap by proposing a Constructionist Computational Creativity (CCC) model. The model is designed to guide the integration of creative AI system-building into K–12 classrooms, supporting the development of both technical and creative competencies. By framing creativity not only as an outcome of learning but also as a pathway into deeper engagement with AI, CCC offers a novel direction for constructionist computing education.

3 METHODOLOGY

This work was motivated by the question of how K–12 students can be enabled not only to use but to design AI-driven Computational Creativity (CC) systems within constructionist learning environments. We approach this question by developing a methodology grounded in both theory and practice. First, foundational theoretical frameworks in CC were analyzed, including Boden's creativity criteria (novelty, familiarity, and value) (Boden, 2004) and Wiggins' formal creativity framework (Wiggins, 2006), leading us to core components of CC systems, which are the following:

Conceptual Space: The set of ideas, artifacts, rules and constraints, and all the concepts that are the fuel of the creative process to explore, transform, and combine into new creative ideas.

Generation Mechanism (Creative Process): The methods or algorithms used to produce new ideas/artifacts; e.g., rule-based systems, evolutionary algorithms, neural networks.

Evaluation Mechanism: A way to assess the novelty, value, or appropriateness of the generated outputs.

Knowledge Representation: The structure and format in which domain knowledge, constraints, and goals are represented; such as semantic networks, and ontologies.

Defined Goal: A clear objective the system is working toward, which can guide the generation and evaluation processes (Wiggins calls this "R", or the set of rules and goals).

To develop the Constructionist Computational Creativity (CCC) model, we synthesized core components of Computational Creativity (CC) systems with constructionist learning principles, such as learning through artifact creation, iteration, and making personally meaningful artifacts. This integration informed the design of our four-stage process: Deconstruct, Design, Create, and Evaluate, explained in the following mapping: in the Deconstruct phase, learners explore existing creative artifacts and ideas within a specific domain to understand the nature of creativity in that context. This exploration helps define the conceptual space by identifying the structure, format, and constraints of creative outputs. Learners also analyze what makes existing artifacts novel and valuable, leading to the formulation of an evaluation mechanism appropriate for the chosen domain. Additionally, this phase involves recognizing the necessary knowledge representations that will later guide the system's generative processes.

The Design phase involves defining a clear creative goal and identifying constraints that reflect the chosen domain. Learners select a generative mechanism suited to their objective and conceptualize how this technique can simulate creativity within the system. This aligns with the generation component of CC systems and prompts students to consider how rules, methods, or algorithms can produce novel outputs.

In the Create phase, students implement the generative mechanism using the data representations that were already decomposed in the deconstruct phase (either in digital or unplugged formats) and apply it toward achieving the previously set goal. This phase brings the generative process into action.

Finally, the Evaluate phase focuses on applying the domain-specific evaluation mechanism to assess the system's outputs, based on the defined goal and creativity criteria of novelty and value, which are observed when deconstructing existing artifacts. Based on this evaluation, learners reflect on their results and refine their systems accordingly, embodying the iterative process central to both CC systems and constructionist pedagogy. This mapping ensures that the experience of building a CC system is not only technically grounded but also aligned with constructionist ideas, providing a hands-on, meaningful learning journey that fosters both creative and computational competencies.

To explore the practical feasibility and educational potential of the CCC model, an exploratory study was conducted with 15 pre-service Computer Science teachers. Participants engaged in an unplugged learning activity centered on designing novel muffin recipes using genetic algorithms. The activity involved identifying the creative domain (culinary recipes), selecting relevant AI techniques, and simulating generative processes through iterative mutation, crossover, and evaluation, all within a set of constraints such as dietary requirements.

The intervention was evaluated through both quantitative and qualitative methods. A structured survey assessed participants' understanding of CC components, clarity of technical processes, engagement potential for students, and anticipated classroom applicability. Complementary reflective discussions provided pedagogical insights into implementation challenges, adaptation needs, and the model's perceived value for teacher preparation and student learning. Based on this feedback, the CCC model was iteratively refined to better support its integration into K–12 educational contexts.

4 OUTLINING A GENERALIZED MODEL FOR CREATING A COMPUTATIONAL CREATIVITY SYSTEM

We present a four-phase model that guides the construction of creative artifacts through the development of Computational Creativity (CC) systems. The model provides a formalized structure that can be used within constructionist learning environments to support learners in exploring both creative domains and fundamental AI concepts. The model is shown in figure 1 below.

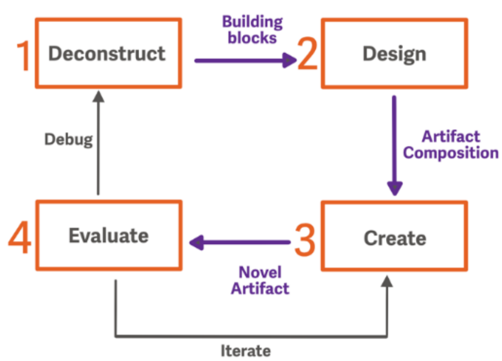

Figure 1: Constructionist Computational Creativity (CCC) model.

Phase 1: Deconstruct: The goal of the first step is to understand creative domains by systematically analyzing and deconstructing existing artifacts. This process serves to help learners identify key components, structural patterns, and creative techniques within a given domain (such as poetry, music, narrative writing, culinary recipes, or visual arts) based on representative examples. By observing and reflecting on existing works, learners begin to recognize the underlying logic and design principles that characterize creative artifacts. The goal of this phase is to extract essential building blocks of the creative artifacts. These include:

- *Data components:* identifying data items that form the creative artifacts such as musical notes, words of poetry, or ingredients in food recipes, and then represent them in digital or unplugged medium.
- *Patterns and relationships:* understanding how elements are repetitively connected to contribute to the final composition, and then represent this pattern either as data structure or rules that controls the creation for a new artifact, either digital or unplugged representation.
- *Novel elements:* understanding domain-specific strategies and rules to create novel artifacts, novelty could be harmony in music, metaphor in literature, food chemical rules in recipes, or word rhyming in poems, achieving this novelty could be through defining certain rules that controls the algorithm that forms the new artifact, or manipulating the data that the artifact consists of, in this phase, students decide or "what" but not "how" which will be defined in the next phase. Of course, there could be more than one novel element, but choosing the important elements that make the artifacts creative is a part of defining creativity in any domain (Jordanous, 2012).

For example, in the context of culinary creativity, learners may begin by identifying common ingredients used in specific types of recipes, such as flour and butter in baked goods. Through comparison across multiple examples, they observe and extract typical patterns (e.g., base ingredients, preparation methods) and locate creative variance (e.g., the inclusion of unique spices or substitutions). This structured deconstruction enables learners to understand how creativity manifests in the domain and prepares them to externalize relevant features as input for AI-based generation processes. As such, this phase supports the translation of implicit creative knowledge into a format suitable for computational modeling (Brüggen, 2018).

Phase 2: Design: Once students have identified the core elements of creative artifacts, the next step is to conceptualize a computational system capable of generating similar outputs. This involves making the observed components explicit through representation of data and operations that aligns with the domain's creative principles (Boden, 2009), resulting in the following composition:

- *Setting a goal:* deciding on the characteristics or features of the creative artifact to be created, such as shape, size, or type.
- Defining constraints: creativity often operates within a set of rules (Boden, 2004), these rules can be stylistic (e.g., adhering to a particular poetic form) or functional (e.g., developing a recipe for a person with a chronic disease), these constraints are set according to observed patterns in deconstruct phase.
- *Identifying the type of creativity:* this will play a role in choosing which aspect of novelty to be created in this CC system and will participate in choosing a suitable AI technique. Creativity techniques as discussed by many researchers (Boden, 2004; Wiggins, 2006; y Pérez, 2015), are considered as following:
    - Combinatorial creativity: merging existing ideas in novel ways (e.g., fusing different artistic styles to create hybrid visual artworks, or fusing different cuisines to create a new dish).
    - Exploratory creativity: navigating structured possibilities within defined constraints (e.g., generating a chess game plan according to known chess game moves).
    - Transformational creativity: redefining creative boundaries to introduce entirely new forms (e.g., developing AI-generated poster design that is inspired by a sunset scene).

- *Establishing an evaluation mechanism:* according to observed patterns in existing artifacts which are widely used and accepted by the human taste, students formulate criteria to evaluate the quality and effectiveness of generated artifacts based on domain-specific metrics, either already existing in defined rules, such as chemical compatibility between food ingredients, or according to subjective evaluation such as sound music harmony.

By formalizing these aspects, students lay the format for an AI-based method capable of producing creative outputs that are meaningful within the chosen domain.

Phase 3: Create: In this phase, students transition from conceptual design to the actual creation of the CC system, whether it was digital, using block-based programming, or unplugged activity using school stationary. First, use the input data for the CC system that was analyzed in the deconstruct phase, then select and apply a generative AI technique that is suitable to the creativity to be represented, using AI methodologies such as:

- *Evolutionary algorithms:* simulating iterative refinement by mutating and optimizing creative outputs over multiple generations.
- *Generative Adversarial Networks (GANs):* Training AI models to generate creative content, by creating a generator and a discriminator that learns to distinguish between good and bad generated output.
- *Markov chains and Recurrent Neural Networks (RNNs):* Employing sequence-based or stochastic-based learning to generate coherent text, rhyming poetry, or speech patterns.

Finally, applying rules and constraints that were defined in previous steps. students will end up creating a system that has data representations, algorithmic representation, and novelty representation through rules and constraints, and these rules and constraints could include controlled randomization as randomization was frequently observed in creative systems to foster novelty among new artifacts (Rubin, 2012).

Phase 4: Evaluate: Evaluating a creative product is inherently complex due to its subjective nature, but its evaluation is fundamental to the process of producing it (Candy, 2013). There are a variety of initiatives among researchers to find a more formal definition of creativity evaluation, especially with AI producing creativity (Jordanous, 2012). Humans' informed judgment and contextual reflection in evaluating creative products is one way to consider a CC system's creativity especially for creative aspects that are complex to be defined empirically (Jordanous, 2012).

Many aspects of creative artifacts can be evaluated and multiple evaluation techniques can be adopted by students with coordination with their teachers, we suggest two examples of evaluation:

- *Objective evaluation:* applying predefined criteria to evaluate certain aspects such as grammatical correctness in a created text, or evaluation of chemical compatibility of ingredients in food recipes (Issa, 2019), this depends on which part of creativity was demonstrated in the CC system, and whether the creative domain has aspects that can go under a systematic evaluation.
- *Subjective evaluation:* incorporating human assessments and evaluating the output based on audience preferences, for example, assessing a new food recipe, considering the dietary preference of a group of people in a quantitative evaluation.

In this phase, students use the system they created to generate a new artifact, then they use the evaluation criteria that was already defined in design phase, to evaluate the generated artifact, if it achieves the selected goal or not, if it doesn't, students can reflect and modify the system rules, constraints, data representation, or algorithm, to get better artifacts generated by the system.

5 CC IN PRACTICE: AN EXPLORATORY STUDY WITH PRE-SERVICE TEACHERS

We conducted an experiment with 15 pre-service Computer Science (CS) teachers to explore the applicability of the proposed model. To begin, participants were introduced to the concept of CC, including its philosophical foundation as a technical representation of creativity using AI (Boden, 2009), and its applications across various creative fields. This foundational knowledge enabled participants to engage in the activity and provide informed reflections that could help assess the practicality and educational value of the model.

The experiment was structured into two phases: hands-on system creation, and guided discussions. To evaluate the outcomes of the experiment, we evaluated the teacher's understanding of AI concepts; a part of the technical learning objectives in the curriculum presented by Michaeli et al. (2023a), we also ask them to assess the applicability of the model in classrooms, which was presented by the authors as socio-cultural perspective of AI learning objectives.

The session began with discussions on different creative domains such as music, narratives, and culinary arts. Then, teachers explored what types of data are used in each domain (e.g., musical notes, story structures, ingredient lists), the building blocks of creative artifacts (e.g., harmonies in music, ingredient combinations in recipes), the types of creativity that are modeled in each domain (combinational, exploratory, and transformational creativity) (Boden, 2004), How rules and constraints are derived from the analyzed artifacts (e.g., Dietary restrictions, narrating style constraints), which AI techniques are suitable to mimic each type of creativity (e.g., Markov chains for text, genetic algorithms for recipes, Generative Adversarial Networks (GANs) for image/music generation) (Goodfellow, 2020), and what could be a suitable approach to evaluate new artifacts in every field (e.g., subjective preference, adherence to constraints). Teachers went through the phases of the CCC model through an activity that includes creating an unplugged CC system that generates a new muffin recipe. Teachers used 12 muffin recipes from AllRecipes.com and analyzed them into building blocks such as flour type, sweeteners, and fruit or vegetables to understand how muffin recipes are created (Deconstruct). Then they selected an AI technique which is genetic algorithms, an evolutionary AI algorithm in which the outcome evolves through multiple iterations of crossover, mutation, and selection, mimicking human biological evolution (Holland, 1992). Genetic algorithms were previously used to recommend new food recipes (Jia, 2024) and they were widely tested on multiple creative domains, in plugged and unplugged forms (Fernández de Vega, 2014). Teachers were divided into two teams, each team set a different goal, team A chose to create a fully vegan muffin recipe, team B chose to create a muffin recipe based on their personal taste preferences. Each team established a subjective evaluation criterion and decided on evaluating evolving recipes by voting (Design). Teachers implemented an unplugged strategy to simulate the mutation, crossover, and selection processes in genetic algorithms (Create). In selection, they chose parent recipes based on their defined end goals and voting. For crossover, each team developed a customized strategy to combine recipe components, they decided where to split parent recipes to create offspring. For mutation, they used randomization to change two ingredients in the generated recipe. Figure 2 shows photos of teachers engaging with these AI concepts in the activity. Afterwards, participants chose to engage in a subjective evaluation of the recipe, using their own criteria that they previously defined from their understanding of the domain and the goals they had set. As discussed in the previous section, human evaluation can be considered for creative artifacts to evaluate many aspects of creativity, one of them is usefulness of the produced artifacts; a criterion that is commonly referenced in creativity research (Kaufman, 2012). Each team performed heuristic evaluations after three evolutionary iterations, where team A encountered difficulties in their crossover strategy, leading to a final recipe that was new but not appealing. They reflected that more iterations and refined mutations could improve results. Team B created a novel recipe that required minor modifications (Evaluate). After completing the exercise, teachers discussed how the same activity could be redesigned with a different underlying AI technique, such as GANs , where students could play roles to simulate the process of training GANs, simulating the behavior of generators and discriminators. Finally, teachers concluded by discussing how this model can be integrated in k-12 education, with flexibility of applying unplugged, semi-plugged, or plugged activities, allowing for greater learnings about creative domains and AI systems.

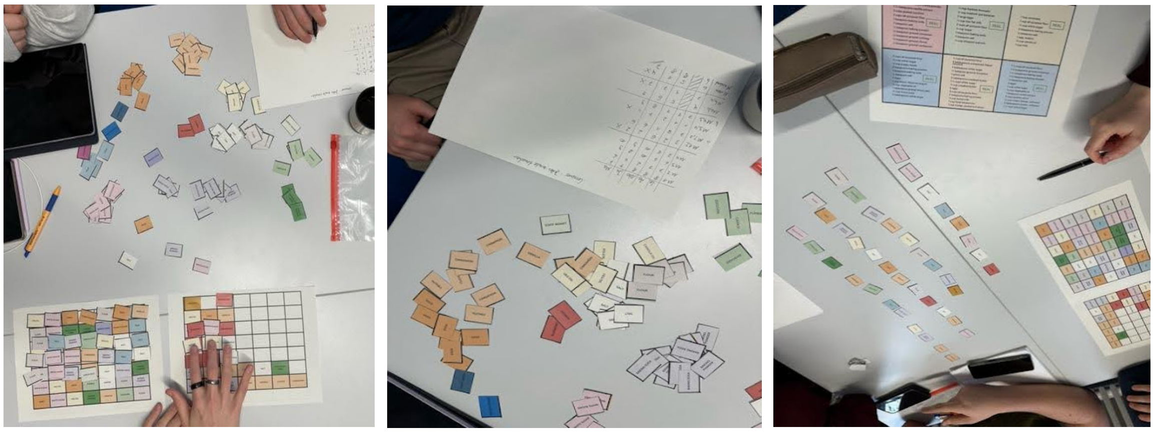

Figure 2: Pre-service teachers designing and experimenting with a constructionist CC-based approach.

6 RESULTS AND DISCUSSION

6.1 Teachers' reflections

Ten pre-service teachers participated in a post-experiment evaluation survey aimed at assessing the perceived effectiveness and applicability of the CCC model. The survey included both quantitative questions covering: (1) understanding of computational creativity system components, (2) perceived student engagement, (3) clarity of the technical process, (4) understanding of AI principles, and (5) likelihood of classroom adoption. All ten teachers found the activity to be interactive and engaging. All participants also demonstrated an understanding of the core components of CC systems. Eight teachers expressed confidence in their grasp of the step-by-step process required to build a CC system. Six reported gaining a clearer understanding of how AI-based systems are constructed to generate creative outputs. Seven participants noted that the activity strongly fostered creative thinking, and nine teachers said they would consider incorporating the activity into their computing or extracurricular classes.

This activity gave teachers an interesting experience to present AI concepts in schools. Through designing and testing their own unplugged creative systems, teachers engaged in reflective practice that not only enhanced their pedagogical content knowledge but also modeled the kind of constructionist learning students would undergo.

6.2 Refinement of the CCC Model Based on Experimental Findings

The experiment and discussion with pre-service teachers revealed several important supporting design considerations that can enhance the model's practical implementation in K–12 classrooms. These considerations do not alter the model's phases, but instead serve as additional practices that support successful adoption:

Student readiness: Participants discussed that students need a foundational understanding of AI (e.g., what AI is, what it can/cannot do). They suggested incorporating a preparatory phase focused on basic AI literacy before starting the CCC activity.

Teacher preparedness: Participants discussed that they could actively shape learning by guiding students' reflections and helping them connect AI techniques to creative outputs. Also, they need to guarantee the technical correctness of choosing AI methods in the CC systems created by students. This could be Emphasized in teacher training in AI and CC facilitation; teachers need scaffolding materials and clear guidance.

Flexibility of activity formats: Teachers discussed plugged, semi-plugged, and unplugged formats depending on classroom needs. They suggested having multiple format options can help them adapt corresponding tools/resources in classroom setups and technical capabilities.

Measuring activity outcomes: Teachers discussed that evaluating students' creativity, and AI understanding will help in measuring the success of the model outcomes. Therefore, teacher training should not only focus on designing and implementing the activity but ways to evaluate the outcomes of the activity, by creating a better understanding of measuring students' AI competencies and creativity.

Using this model, educators can tailor the activities to their technological resources and student needs, while still maintaining the core learning outcomes. Ultimately, the role of the teacher remains central throughout the process, not only in facilitating the activity, but in framing it pedagogically to ensure that students derive AI competencies from their creative work.

7 CONCLUSION

This study presents a structured model for teaching and learning about AI and creative domains through constructing CC systems. By following the four-phase process (Deconstruct, Design, Create, and Evaluate) students gain both theoretical and practical insights into creative domains while actively engaging with AI concepts. This methodology not only enables learners to analyze and create novel and creative artifacts but also fosters deeper understanding through hands-on experimentation and aligns perfectly with the idea behind constructionism which is learning by making. Moreover, this methodology reinforces the connection between technology and creative expression, demonstrating how AI can enhance and support creative fields. The proposed model serves as a valuable reference for designing educational experiences that integrate CC, encouraging students to explore AI's role in creative fields such as literature, music, and culinary arts. Future research could explore how this methodology impacts students' learning outcomes over time and how different creative domains influence engagement and understanding. Ultimately, by embedding CC in education, students are provided with tools to become both creators and critical thinkers of AI-based creativity.

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