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Co-design of analogical and embodied representations with children for child-centered AI learning experiences

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ABSTRACT

AI recommendations shape our daily decisions and our young generation is no exception. The convenience of navigating personalized content comes with the notorious "filter bubble" effect, which can reduce exposure to diverse options and opinions. Children are particularly vulnerable to this due to their limited AI literacy and critical thinking skills. In this study, we explore how to engage children as co-designers to create child-centered experiences for learning AI concepts related to the filter bubble. Leveraging embodied and analogical learning theories, we co-designed an Augmented Reality (AR) application, BeeTrap, with children from underrepresented backgrounds in STEM. BeeTrap not only raises awareness of filter bubbles but also empowers children to understand recommendation system mechanisms. Our contributions include (1) insights into child-centered AI learning using embodied metaphors and analogies as educational representations of AI concepts; and (2) implications for enhancing children's understanding of AI concepts through co-design processes.

1. Introduction

Children growing up in the Artificial Intelligence (AI) age are digital natives with access to AI-recommended information from a very young age. Recommendation systems are the ubiquitous AI technologies that help individuals navigate the ocean of information that matches their interests. The convenience of personalized recommendations comes at a cost that people often lose sight of — isolating individuals from diverse choices and opinions, or the so-called "filter bubble" (Pariser, 2011). Filter bubbles may heavily influence children, from what books to read, and who to befriend on social media, to future education and career opportunities. Imagine a middle schooler who often receives news of NBA players on social media just because of his demographic and friend circles. That student may be "trapped" in the idea of becoming a professional basketball player even though he is also interested in art and science. Children are particularly vulnerable to persuasion from recommendation systems, not only due to their immature critical thinking skills and impulse inhibition (Radesky et al., 2020), but also their tendency to overtrust AI technologies, especially when perceived as an intelligent agent (Druga et al., 2017; Long and Magerko, 2020a).

Daily interactions with AI recommendations, however, do not necessarily help children grasp an understanding of related literacy (Pangrazio and Cardozo-Gaibisso, 2021), let alone develop the capability of making informed algorithmic decisions (Swart, 2021). Although it is needed for children to understand the impact of specific AI ethical issues (Garrett et al., 2020b; Wang et al., 2023a), research shows that young students lack awareness and reflection of intelligent technologies' real-world impact (Schaper et al., 2022; Ito et al., 2023; Lee et al., 2023). To develop a meaningful understanding of such critical AI literacy that can be transferred to personal life context, children must be computationally empowered by learning the underlying AI mechanism (Hitron et al., 2019; Kaspersen et al., 2021b). Being less competent to cope with complex online life confirms the urgency of extending children's critical algorithmic literacy (Livingstone, 2018). Uncovering the AI black box can also increase children's self-efficacy toward AI and develop their capabilities to better utilize AI (Druga, 2018; Kajiwara et al., 2023). Therefore, to make informed and empowered actions in the era of AI, children need to be equipped with major AI literacy around the impact, inner workings, and mitigation strategies of the filter bubble (Sulmont et al., 2019; Schaper et al., 2023). This may further prepare the young generation to meet a growing demand for AI-related computational skills (Druga et al., 2019a; Ng et al., 2021; Zhou et al., 2020) and inspire the next generation of AI researchers and developers (Touretzky et al., 2019).

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Research shows that novice learners intuitively develop datafied or metaphorical representations to embody AI recommendation systems (Alvarado et al., 2021). This and other existing research (Long and Magerko, 2020b) suggest a promising direction of connecting embodied metaphors with abstract concepts around AI recommendation systems to facilitate a smooth transition from novices' prior high-level understanding to accurate and in-depth AI literacy. Embodied metaphors refer to how abstract concepts connect to our bodily experiences, often through unconscious forms (Antle et al., 2009). Researchers have investigated effective embodied experiences for AI learning, including (1) students' physical enactment as data and algorithms (Druga et al., 2019b; Heinze et al., 2010; Sulmont et al., 2019), (2) data collection and evaluation for AI training through learners' gestures and bodily movements (Zimmermann-Niefield et al., 2019, 2020), (3) direct manipulation of tangible representation of AI models and data physicalization (De Raffaele et al., 2018; Kim and Shim, 2022a), and (4) interaction with embodied agents promoting playful bodily experiences (Druga et al., 2017; Jeong et al., 2015). Despite these efforts, research gaps remain in (1) developing more specific mappings between embodied metaphors and individual AI concepts and (2) aligning the embodied metaphors with children's identities, personal interests, and cultural backgrounds (Long and Magerko, 2020b). Such alignment could especially benefit the underrepresented groups (Eaton, 2008). Some recent research sheds light on a potential solution to establish the connection of AI learning with learners' backgrounds — integrating analogical learning with embodied learning (Dai et al., 2023).

Therefore, our work aims to design embodied metaphors and analogies to represent AI concepts around the inner workings and ethical issues of recommendation systems. Through co-design with children, we explore the design of child-centered AI learning experiences that incorporate children's interests. However, without sufficient knowledge of AI, the embodied representations co-designed by novice users remain high-level and lack the underlying AI mechanisms (Alvarado et al., 2021). With children being unfamiliar with both the target learning objectives of AI literacy and the theories of embodied & analogical learning, it could be very challenging to involve young learners in the co-design process to probe their authentic preferences and needs in the learning design.

To tackle the challenges, we created a baseline design of BeeTrap (Zhou et al., 2024), a novel Augmented Reality (AR) application, by co-designing with AI experts. BeeTrap aims to provide a playful, embodied, and analogical learning experience for children to grasp concepts around AI recommendation systems and filter bubbles (Gong et al., 2024). Built upon the iterated design of BeeTrap, we conducted two co-design workshops with 11 high school students and nine middle school students from underrepresented backgrounds in STEM. Our co-design study investigates three critical research questions:

RQ1 What are children's preferences for analogical and embodied representations that concretize AI concepts around the filter bubble in familiar science subject areas?

RQ2 What new analogical and embodied representations do children create through co-design and what are the underlying learners' needs?

RQ3 How does engaging as co-design partners impact children's learning experiences of target AI concepts and their potential to expand their understanding?

There are two main contributions made by this work:

1. This work provides design insights for child-centered AI learning experiences based on: (1) children's preferences for embodied metaphors and analogies as educational representations of AI concepts, (2) children's new creations that bridge gaps in the original representation design, and (3) enhancements in social interactions, gamification, and the incorporation of children's interests.
2. Our findings highlight the potential of co-design in helping young learners deepen their understanding of newly acquired AI knowledge, ask more insightful questions about AI, and even develop an initial grasp of advanced AI concepts beyond the original learning objectives.

2. Related work

2.1. Teaching children about AI recommendation systems

Despite the importance and challenges of teaching children about filter bubbles and related inner workings, limited technologies have been designed (Lee et al., 2023; Schaper et al., 2023). To explore how informal art exhibitions can support learners' critical thinking over ethical aspects of AI, researchers have designed art exhibitions to provide youth with artistic first-person experiences of both the positive and negative impacts related to AI recommendations (Lee et al., 2023). Workshops are also developed for children to redesign YouTube's recommendation system by identifying different stakeholders (Ali et al., 2019; DiPaola et al., 2020), for teenage girls to consider how existing and future AI recommendations can impact challenges in their lives (Solyst et al., 2022), and for children to learn about online datafication and coping mechanisms (Wang et al., 2023b). Researchers have also created structured classroom curricula to deliver AI-related ethical knowledge (Garrett et al., 2020a). Existing research recommends teaching kids about AI by (1) guiding them to reflect upon real-world ethical dilemmas between the convenient personalized experience and the loss of control and diversity in AI recommendation systems and (2) empowering them to take action to tackle the filter bubble (Schaper et al., 2023).

Most research touches on developing a conceptual understanding of the ethical concern, leaving a gap in how to design educational tools for young learners to investigate the inner workings causing filter bubbles and its potential mitigation strategy. To fill the gap in unveiling the black box underlying filter bubbles, we designed an educational application to teach children about AI concepts centered around filter bubbles, AI recommendation systems' inner workings, and diversification as a mitigation strategy.

2.2. Embodied learning for AI education

Embodied learning can develop a deeper comprehension of the material (Macedonia, 2019), by promoting cognitive functions such as attention, memory, and problem-solving through bodily experiences (Kiefer and Trumpp, 2012; Shapiro, 2014). Existing embodied learning research has investigated supporting high-dimensional data analytical process by inviting students to position in a physical space representing a 2D projection (Bilstrup et al., 2022; Chen et al., 2018) and by distributing the demanding cognitive load in 3D spatial immersive environments for better sense-making of complex data (Ens et al., 2022). Researchers have explored how concrete 3D models can reify multidimensional data (Kim and Shim, 2022b), how body gestures can support data collection, and other steps in the pipeline of AI model training (Carney et al., 2020; Long et al., 2021a; Zimmermann-Niefield et al., 2019; Kaspersen et al., 2021a), and how tangible user interface elements and spatial metaphors can embody abstract components involved in the neural network (De Raffaele et al., 2018), semantic networks, and the feature-based machine learning algorithm (Long et al., 2021c).

AR is a powerful embodied interface that allows learners to physically enact an abstract concept and enhance understanding (Radu, 2014). Novice learners find it intuitive to perceive the experience of being trapped by similar data and require the design of recommendation systems to demonstrate how they are built over iterations (Alvarado et al., 2021). This study used AR to create embodied metaphors for abstract concepts centered around the impact, inner workings, and mitigation strategy of filter bubbles. Existing research in math education shows that physical distance and walking steps can enhance children's mathematical thinking (Tran et al., 2017), which is one of the major learning barriers for young students to develop AI literacy (Zhou et al., 2020; Druga et al., 2019a; Kahn et al., 2018).

2.3. Analogical learning for AI education

Analogical learning is a cognitive process in which people connect concepts in a familiar source domain and concepts in an unfamiliar target domain for learning (Clement, 2013; Gentner and Smith, 2013). An existing work used water flow as an analogy for electricity to create a more accessible experiment space with electricity building blocks augmented by virtual water flow (Kreienbühl et al., 2020). Analogical learning may increase student engagement and motivation in activities through students' closeness with source domains (Thiele and Treagust, 1994; Schaper et al., 2022). Furthermore, analogies are often related to the physical world and concrete representations. This implies the potential for combining with embodied interaction (Dai et al., 2023) in an AR learning environment.

Analogies are commonly used to aid students' conceptual understanding, but more research is needed to explore how analogies can help young learners grasp abstract AI concepts. Existing work has proposed using human intelligence as an analogy for machine intelligence through role-play and embodied cognition (Dai et al., 2023; Druga et al., 2019a; Zhou et al., 2020). However, equating human thinking with computer processing may reinforce an anthropomorphic view of AI, potentially leading to misconceptions and hindering learning (Sulmont et al., 2019; Mertala et al., 2022). To address this, this work investigated how analogies from K-12 science topics can support AI learning. K-12 science topics may provide a shared foundation for analogical reasoning, benefiting diverse learners (Baron and Sternberg, 1987; Lee et al., 2023; Matthee and Turpin, 2019). Young learners naturally use analogies and metaphors in scientific discourse (Kesner Baruch et al., 2016). We chose bee pollination, a common K-12 science topic (States, 2013), as the base domain for analogies in the BeeTrap learning experience.

2.4. Co-design with kids

The Interaction Design and Children (IDC) and co-design communities have developed various techniques for co-designing with children, including fictional inquiry (Dindler and Iversen, 2007; Hiniker et al., 2017), big papers (Guha et al., 2004), bags-of-stuff (Yip et al., 2013), comicboarding (Hiniker et al., 2017; Moraveji et al., 2007), stickies (Yip et al., 2013; Christensen and Abildgaard, 2021), obstructed theater (Read et al., 2010; Walsh et al., 2013), mission from mars (Dindler et al., 2005), layered elaboration (Walsh et al., 2010), KidReporter (Bekker et al., 2003), paper prototyping (Slegers and Donoso, 2012), storyboarding (Truong et al., 2006), and Stop Motion Studio (Sanoubari et al., 2021). These techniques aim to make the design process engaging and enjoyable. They differ in partner experience, accommodation needs, design space, design maturity, cost, portability, technology level, and physical interaction (Walsh et al., 2013).

During the co-design with children, a wide range of children's roles can be considered (Iversen et al., 2017). For example, when researchers seek support for future technology design and a better understanding of children's learning process, children play the role of a user or a tester to be observed and tested during the participatory process. To involve children's voices directly in the design process, researchers invite children as design partners in various design sessions with a shared goal of designing new technology. In this study, we engaged young students as testers, informants, and design partners (Famaye et al., 2024; Walsh et al., 2013). Initially, we evaluated and expanded upon a baseline design—an initial set of analogical and embodied representations created by researchers—using input from middle and high school students. As testers, students interacted with technology prototypes and provided direct feedback. In the role of informants, they actively participated in structured discussions to offer design insights through collaborative dialog. Finally, as design partners, students contributed their creative ideas for improving the technology, developing new elements through material crafting and other co-design activities.

Given (1) students' lack of prior experience with co-design practices, (2) the relatively constrained design space defined by the baseline design, (3) the inclusion of advanced technical concepts such as AI recommendations, and (4) the possibility that children from underrepresented STEM backgrounds may be unfamiliar with AR technology, we selected two co-design techniques: layered elaboration (Walsh et al., 2010) and storyboarding (Truong et al., 2006). Layered elaboration provides a structured approach for iterative design within a defined design space, allowing participants to build on existing ideas. Storyboarding situates problems and solutions in context, making complex concepts more accessible to novice designers. It is also particularly suited to design phases where a baseline design has already been established.

3. BeeTrap: The baseline design for co-design with children

3.1. Target learning objectives

BeeTrap (Zhou et al., 2024) focuses on three learning goals: (1) comprehending the filter bubble effect, (2) understanding the mechanisms behind filter bubbles in AI recommendations, and (3) using a diversification algorithm to break filter bubbles. The learning goals are based on content-based recommendation systems, which suggest items based on features that match user profiles (Aggarwal, 2016b; Pazzani and Billsus, 2007; Ricci et al., 2015).

First, the filter bubble is an ethical concern where users are presented with content that closely mirrors their previous selections (Gao et al., 2022). This results in decreased information diversity and limited user choices within recommendation systems. *Second*, the inner workings of content-based recommendation systems that cause filter bubbles are explained. This involves tracking user selections, matching user profiles with available items, ranking these items based on their similarity to the user profile, and recommending the highest-ranked items (Aggarwal, 2016a; Jannach et al., 2010; Lu et al., 2015; Pazzani and Billsus, 2007). *Third*, a diversification algorithm mitigates filter bubbles by expanding the ranking list of items and re-ranking them based on diversity (Kunaver and Požrl, 2017; Ziegler et al., 2005). This diversity can be measured as the average distance between item pairs (Premchaiswadi et al., 2013), resulting in a more varied set of recommendations.

3.2. Iterative design process

Our design methodology is rooted in design thinking principles (Liedtka, 2018), focusing on iterative development and evaluation. In the initial phase, we collaborated with AI experts to brainstorm ideas, which led to the creation of BeeTrap V1. This version incorporated analogies such as a garden, flowers, bees, and an environmental scientist, along with the NEAR-FAR embodied metaphor (Hurtienne and Israel, 2007).

Next, we carried out a proof-of-concept evaluation of BeeTrap V1 with middle-school students and a focus group interview with K-12 science teachers. This phase began with participants engaging with BeeTrap V1 to understand the analogies, metaphors, and AI concepts involved in BeeTrap. The insights gained from this stage informed the improvements in BeeTrap V2, including the addition of new analogies such as a beehive, flower buds, and pollen. Section 3.3 introduces design details.

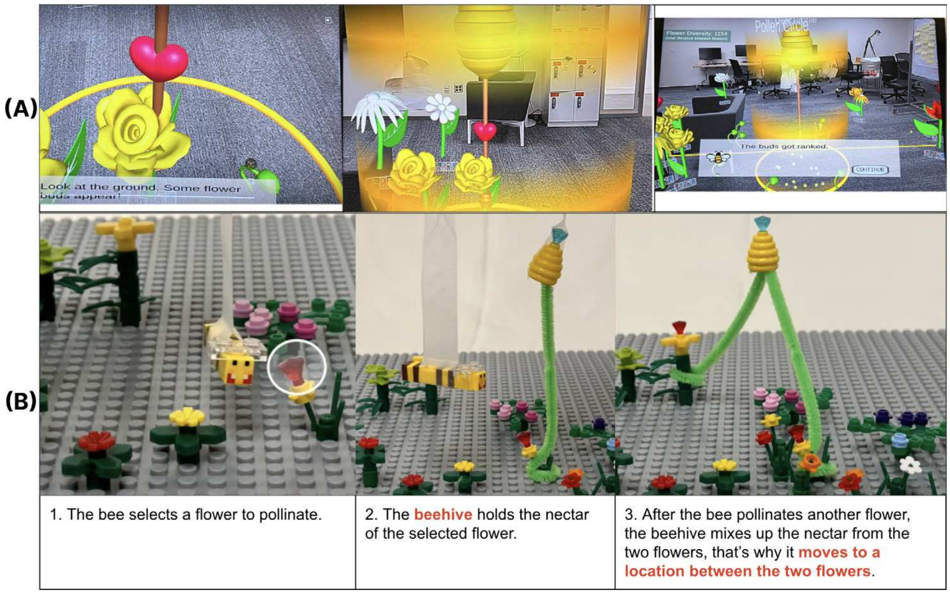

Fig. 1. (A) AR interfaces and (B) third-person view stop-motion video demonstrating the representations of the user profile.

3.3. Major analogies and embodied metaphors in BeeTrap baseline design

BeeTrap has three sets of analogies and metaphors, representing the user profile in AI recommendation systems, similarity-based ranking to generate recommendations, and the diversification algorithm to break filter bubbles.

The user profile in a content-based recommendation system uses the aggregated vector of user-selected items. The beehive that contains pollen from pollinated flowers serves as the analogical representation of the user profile; the beehive moves to the center point of locations where pollinated flowers are projected, which serves as the embodied representation of how the user profile is updated based on the items selected by the target user (Fig. 1).

Similarity-based ranking identifies items most similar to the user profile (Pazzani and Billsus, 2007). The pollen circle size is an embodied representation of the range of similarity between the newly recommended items and the user profile (Fig. 2). For example, a smaller pollen circle represents recommending items that share higher similarity with the aggregated vector of the user profile. The set of flowers around the beehive is an analogical representation of items most similar to the user profile.

The diversification algorithm mitigates the filter bubble effect. It mainly involves two steps: (1) enlarging the ranking range to include more diverse items for recommendation, and (2) ranking the items based on diversity instead of similarity. There are two underlying embodied representations. *First*, enlarging the pollen circle represents enlarging the ranking range of items to include more diverse items for consideration (Fig. 3). *Second*, switching from locating the most clustered flowers to the sparsest flowers represents changing from similarity-based ranking for recommendation to diversity-based ranking (Fig. 4).

Table 1
Basic demographic information of high school students in co-design workshop #1 (s1p1-s1p11) and middle school students in co-design workshop #2 (s2p1-s2p9).

PID	Gender	Grade	Race
s1p1	Female	12th	White/Caucasian
s1p2	Female	11th	Hispanic
s1p3	Female	11th	Hispanic
s1p4	Female	11th	Black or African American
s1p5	Male	11th	Turkish
s1p6	Male	11th	Asian/Pacific Islander
s1p7	Male	9th	Hispanic
s1p8	Male	11th	Asian/Pacific Islander
s1p9	Female	12th	Black or African American
s1p10	Male	11th	Hispanic
s1p11	Female	11th	Black or African American
s2p1	Female	8th	Black or African American
s2p2	Male	7th	Black or African American
s2p3	Male	7th	Black or African American
s2p4	Female	8th	Black or African American
s2p5	Female	8th	White+Black
s2p6	Female	6th	Asian+Black
s2p7	Male	8th	White+Black
s2p8	Male	10th	Black or African American
s2p9	Male	10th	Black or African American

4. Research method: Co-design with children

4.1. Goals and methodology

To create more effective representations of AI concepts for learning, this study aims to understand young learners' perception of educational analogical and embodied representations of target AI concepts and their learning needs within the technology-supported learning experience (Kodama et al., 2017). Given the complexity of AI concepts, traditional methods such as interviews and surveys may no longer be sufficient to capture learners' perceptions or provide as detailed and insightful data as co-design techniques with children (Westcott and Littleton, 2005; Woodward et al., 2018; Walsh et al., 2013; Yip et al., 2019).

Existing co-design research of AI learning has engaged K-12 teachers to integrate AI for their classrooms (Lin and Van Brummelen, 2021) and family groups to communicate AI concepts through museum experiences (Long et al., 2021b). There is a lack of involvement of children, the major stakeholder, in the creation and iteration of AI learning experiences (Sanusi et al., 2023; Yue et al., 2022).

Our study used co-design to empower children to evaluate, reflect on, and express their abstract ideas about the embodied learning experience more tangibly and expressively. We applied two co-design techniques: layered elaboration (Walsh et al., 2010) and storyboarding (Truong et al., 2006).

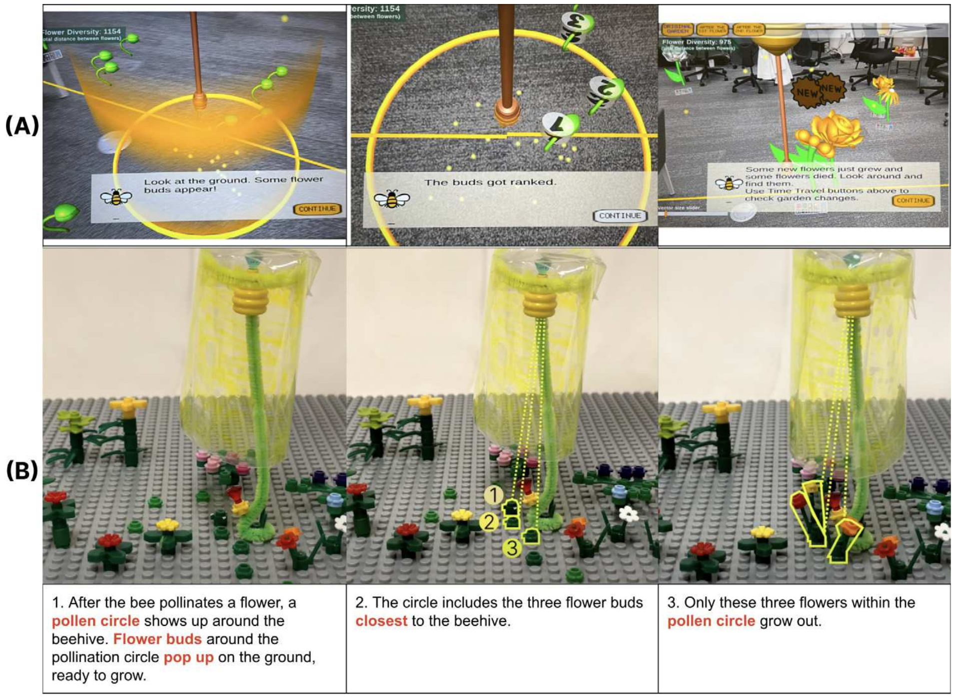

Fig. 2. (A) AR interfaces and (B) third-person view stop-motion video demonstrating the representations of similarity-based ranking in content-based recommendation systems.

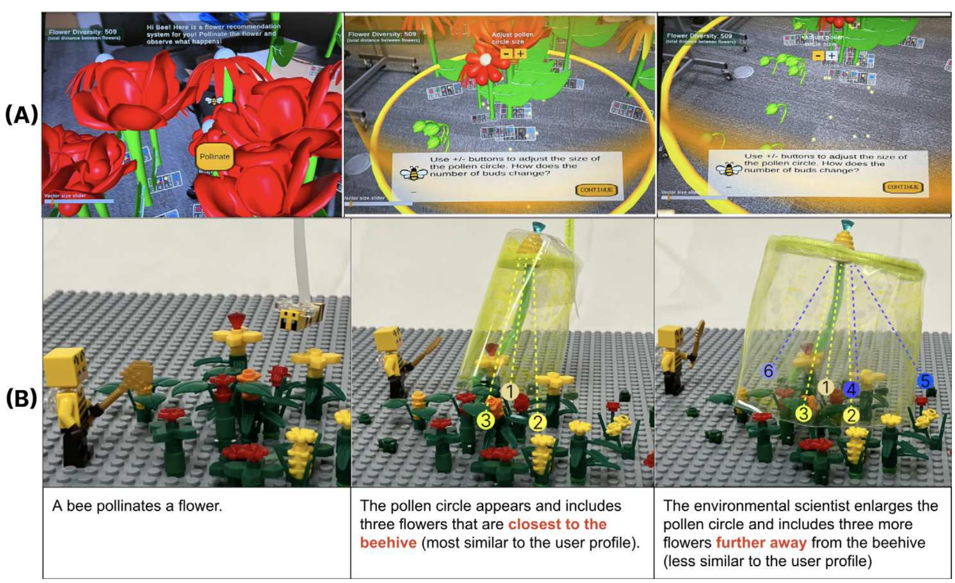

Fig. 3. (A) AR interfaces and (B) third-person view stop-motion video demonstrating the representations of enlarging ranking range for diversification.

4.2. Participants

We recruited the first group of 11 students from a summer camp for high school students with lower socioeconomic status from the urban school district in upstate New York (Table 1 s1p1-s1p11). The second group consisted of nine middle school students from a summer camp in an ethnically and economically diverse urban school district in upstate New York (Table 1 s2p1-s2p9). Before the study, each student was informed about the procedure, acquired parental permission, and signed an assent form. This study was approved by the Institutional Review Board (IRB).

4.3. Study procedure

Prior work posits that children and novices may encounter challenges when expressing their thoughts, and proposes incorporating additional organization into the process by promoting the generation of ideas through incremental steps (Guha et al., 2004). Therefore, to reduce participants' cognitive load, we divided the sessions of experiencing existing designs and design activities into smaller portions of the entire system design. With two different groups of participants, we conducted two co-design workshops on-site during summer camps. Each workshop contained three sessions (Table 2) with detailed procedures described below.

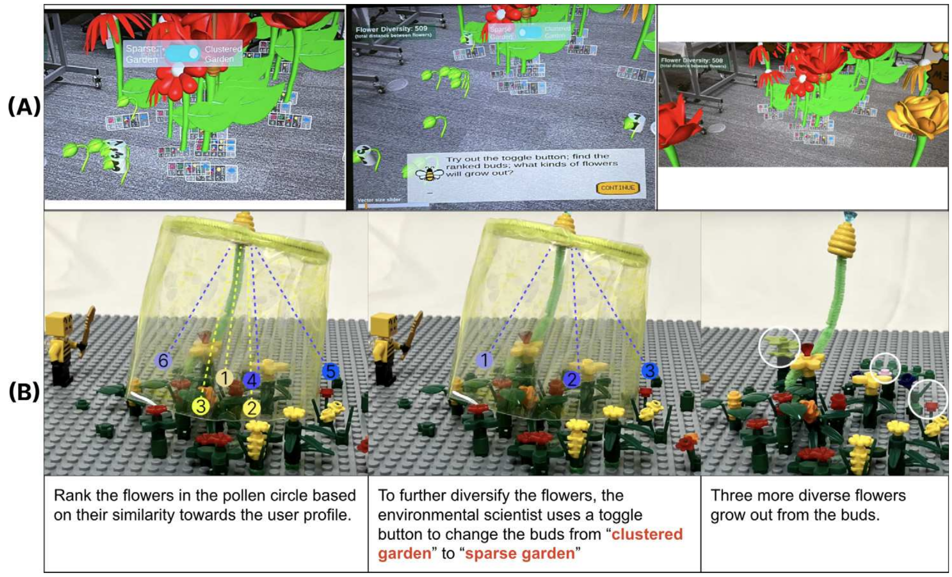

Fig. 4. (A) AR interfaces and (B) third-person view stop-motion video demonstrating the representations of diversity-based ranking for diversification.

4.3.1. *Session 1: Children experience BeeTrap activities*

The challenges in co-designing educational analogical and embodied representations of AI concepts with children are two-fold. *First*, children tend to have existing misconceptions and a significantly steep learning curve associated with complex AI concepts (Hitron et al., 2019; Kaspersen et al., 2021a; Kodama et al., 2017; Valero-Mora and Ledesma, 2011; Chen et al., 2018). *Second*, young students may lack digital literacy to use novel digital interfaces, such as AR technology, as necessary design materials to afford analogical and embodied learning experiences. To address these challenges, in the first session, we invited students to experience three mobile-based AR learning activities that use pre-designed analogical and embodied representations. The learning objectives of the three activities are to understand: (1) the filter bubble effect; (2) the inner workings of content-based recommendation systems; and (3) the basic diversification algorithm to mitigate the filter bubble effect. More details about each activity are described as follows.

Filter bubble experience. Students started by learning how to navigate the virtual garden using a tablet, to reduce a flower diversity score seen in the top-left corner of the screen to below 800. As they took on the roles of "bees", they decided which virtual flowers to pollinate, focusing on attributes like color, petal size, and shape outlined in the flower's data vector. Students utilized a "time travel" function to revisit previous states of the garden, observing the effects of their choices across different stages.

Inner workings of a content-based recommendation system. Students went through four rounds of pollination in the virtual garden. In the first two rounds, they were guided to observe and vocalize their understanding of various design metaphors including the distance between flowers, the characteristics of the flower buds, and the pollen circle. In the subsequent two rounds, students answered the five on-screen multiple-choice questions that probed their understanding of the recommendation mechanism. The questions, designed to appear twice, encouraged students to think deeply about the representation and mechanics of the recommendation system presented through the AR garden.

Diversification to break filter bubbles. Students were tasked with increasing the flower diversity score of the virtual garden. The task was framed as an effort to break out of a "filter bubble" observed in previous sessions. Students switched between two roles: one as a "bee" seeking diverse flowers, and the other as an "environmental scientist" tasked with encouraging a healthy ecosystem for the bee by achieving a diverse garden. When roleplaying the scientist, students manipulated the pollen circle size and controlled the flower growth distance (far away from or close to the beehive). Then students moved close to flowers to pollinate, with the choices directly affecting the garden's state. The session concluded once students raised the diversity score above a set score over several trials.

Throughout Session 1, three researchers resided in two rooms to assist students with the study procedure when requested. This session lasted for about 40 min in total (Table 2(1)). It aims to prepare students for co-design with both necessary AI literacy and experience of mobile-based AR technology. In addition, the analogical and embodied representations implemented in the mobile-based AR application serve as a design baseline for students to comment on and create new designs in Sessions 2 and 3.

4.3.2. *Session 2: Children annotate the likes and dislikes of existing designs through the adjusted layered elaboration*

Layered elaboration (Walsh et al., 2010) uses transparent layers to preserve the original design while facilitating iterative improvements for paper-based prototyping. In this session, we adopted and adjusted the method of layered elaboration to collect students' likes and dislikes of major embodied and analogical representations in BeeTrap.

Students first watched a stop-motion video clip filmed with Lego blocks. The Lego blocks were arranged in individual frames of the stop-motion video to demonstrate existing designs of analogical and embodied representations. The stop-motion video aims to create a more authentic and engaging third-person view of representatives involved in (1) the filter bubble effect (Fig. 5.A), (2) AI recommendation algorithm (Fig. 5.B), and (3) breaking the filter bubble with a diversification algorithm (Fig. 5.C).

During the layered elaboration, students worked in small teams of two to four, annotated what they liked and disliked about individual representations in BeeTrap, and drew design improvements on a transparent sheet placed over the design baseline (Fig. 6.1). Within each team, students communicated their ideas, asked follow-up questions, and built upon each other's ideas. We adjusted the layered elaboration technique for our research and design purposes by using the existing analogical and embodied representations as the design baseline for students to comment on, rather than asking students to create a new design from scratch. This is due to the challenges mentioned in Section 4.1 for children to co-design representations of abstract AI concepts.

Table 2
The overview of the three-session study.

Session	Activities
(1) Session 1	(a) Pre-survey; (b) BeeTrap learning activities: filter bubble experience, inner workings of a content-based recommendation system, diversification to break filter bubbles; (c) post-study interviews.
(2) Session 2	Annotating likes and dislikes through layered elaboration.
(3) Session 3	Co-designing new analogies and metaphors through storyboarding.

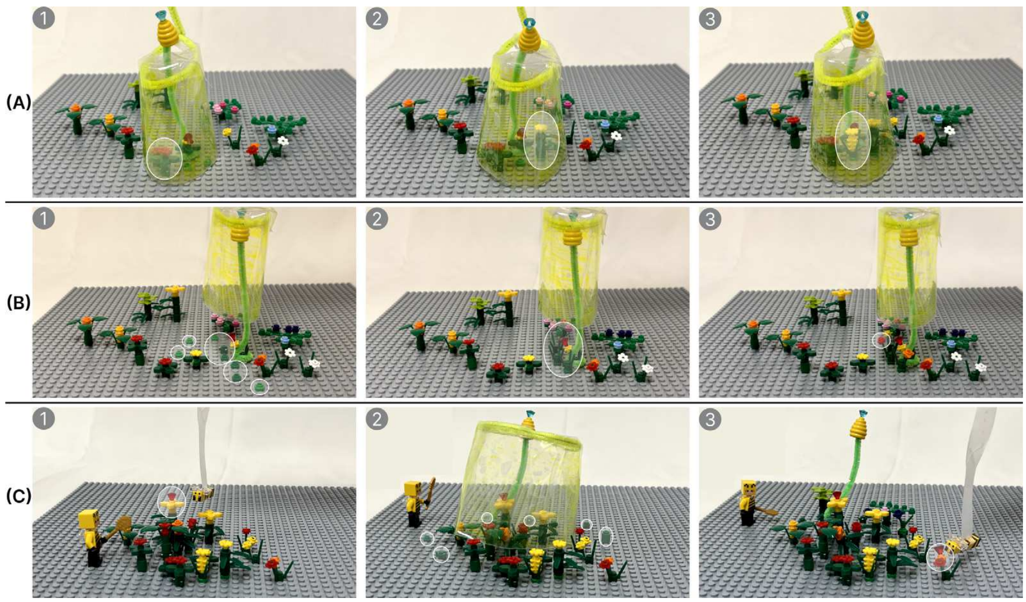

Fig. 5. Key frames from the stop-motion video clip that demonstrate major analogical representations in BeeTrap: **(A)** the filter bubble effect: after the bee pollinates a flower, (1) the first new flower grows out; (2) the second new flower grows out; (3) the third new flower grows out. **(B)** the AI recommendation algorithm: after the bee pollinates a flower, (1) flower buds appear on the ground; (2) the bud closest to the beehive grows into a new flower; (3) the bud second closest to the beehive grows into a new flower. **(C)** breaking the filter bubble with a diversification algorithm: (1) a bee pollinates a flower; (2) the environmental scientist enlarges the pollen circle to rank more flower buds; (3) a new flower farther from the beehive grows out and get pollinated by the bee.

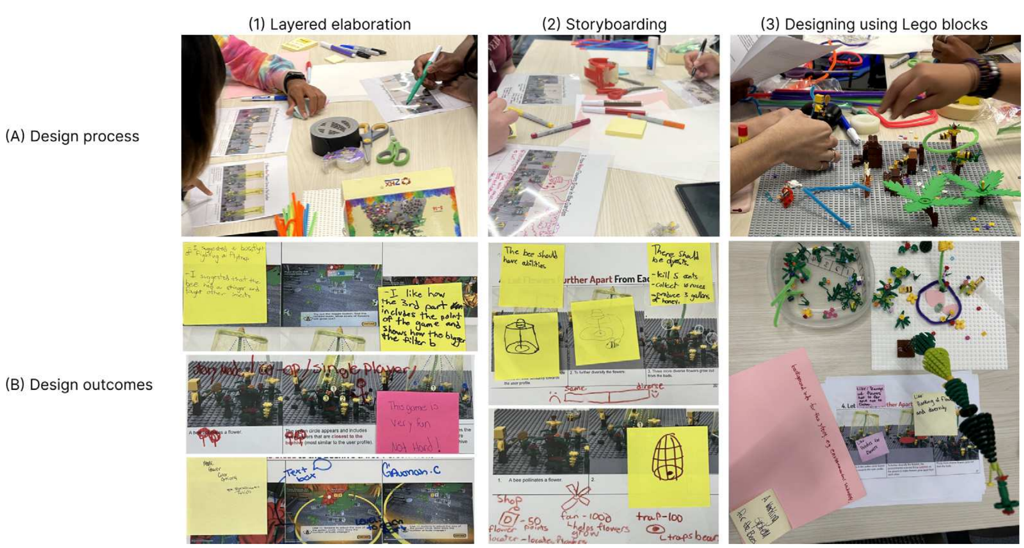

Fig. 6. Processes and outcomes from co-designing through (1) the adjusted layered elaboration, through (2) storyboarding, and by using (3) Lego blocks.

Crafting materials include transparent sheets for annotation and drawing, markers, sticky notes, and the printouts of four design baselines for user profile (Fig. 1.B), similarity-based ranking for content-based recommendation systems (Fig. 2.B), ranking range of items for recommendation (Fig. 3.B), and diversity-based ranking for mitigating the filter bubble effect (Fig. 4.B).

4.3.3. Session 3: Co-design through storyboarding

Storyboarding (Truong et al., 2006) is a co-design technique where the story of a system design is drawn onto large sheets of paper to establish a timeline as well as the aesthetics of the system. This technique puts problems and solutions in context and makes them easier to understand. This method is effective in capturing diverse perspectives, fostering creativity, and visually conveying complex ideas

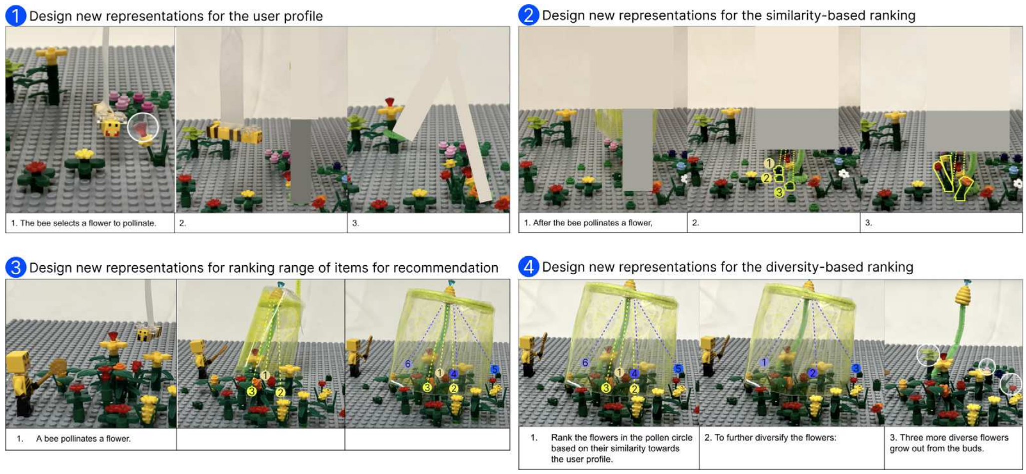

Fig. 7. Storyboards with blank spaces for children to create new representations of different AI concepts involved in AI recommendation systems' inner workings and the filter bubble.

or solutions. This session aims to refine prioritized design elements and innovate new designs.

Students were introduced to the session's objectives and given an overview of the storyboarding process. Then they captured ideas and visualized concepts by filling out blank spaces in the storyboards. The blank spaces here demonstrated the design space for creating new ideas. Students were organized into small groups to share ideas, ask follow-up questions, and suggest new ideas to add on. Each group was provided with paper, pens, markers, and print-outs of storyboards to be filled out (Fig. 7). In the end, students finished drawing in the storyboards to demonstrate their new design ideas of analogical and embodied representations, adding brief descriptions if needed (Fig. 6.2). They could choose to demonstrate their ideas by using Lego blocks instead of sketching (Fig. 6.3). Throughout the session, researchers guided the process, ensuring that participants stayed focused on the design objectives and that the environment remained conducive to creativity and collaborative learning.

4.4. Data collection

In the co-design workshops, we gathered a diverse range of data across various mediums for analysis. We photographed participant-generated artifacts, such as annotations on existing designs, sketches of new designs, written feedback on prototypes, and design artifacts built with Lego blocks. We video and audio-recorded participants' interactions to capture detailed insights from their design processes and group discussions. One researcher transcribed the audio recordings by using Rev, an online transcription service. Two researchers reviewed the transcripts along with the video recordings for manual correction and further analysis. Some dialogs were not captured due to inaudibility, overlapping speech, and the logistical challenge caused by the limited number of recorders among co-design tables. Nonetheless, the visual data from the design artifacts served as a supplementary source, compensating for gaps or unclear segments in the audio recordings.

4.5. Data analysis

Given the limited number of study participants, we steered clear of quantitative comparisons and statistical analysis, recognizing that such results would lack statistical significance. We focused on qualitative analysis, which is more appropriate for exploring complex, nuanced perspectives from co-design and gaining a deeper understanding of this novel research field (Braun and Clarke, 2006).

We conducted a thematic analysis (Braun and Clarke, 2006) on the transcripts of the video recordings of the co-design sessions and the design artifacts to answer three research questions. For **RQ1** and **RQ2**, we analyzed students' preferences for analogies and metaphors of AI concepts and their design creations. Through line-by-line coding of the transcripts and the analysis of visual and textual elements of the artifacts, we extracted specific aspects of the analogies and metaphors that students liked and disliked, as well as all the design improvements and new design ideas they generated. For each design that children commented on, two researchers independently coded the data and grouped the codes into higher-level themes. Through regular meetings, two researchers compared individual codes, discussed their emerging themes, and resolved disagreements.

For **RQ3**, we focused on students' understanding of the concepts related to AI recommendation systems and the filter bubble effect. Using the same thematic analysis approach, two researchers coded the transcripts independently and discussed their annotations to reach a consensus. A third researcher joined to further confirm and refine the themes, ensuring that the themes were well-supported by the data and accurately represented participants' understanding of the concepts.

5. Results

5.1. RQ1. What are children's preferences for analogical and embodied representations that concretize AI concepts around the filter bubble in familiar science subject areas?

This section elaborates on four themes in children's likes and dislikes of the representations of AI concepts: (1) the interrelations between analogical & embodied representations are effective scaffoldings; (2) children enjoy vibrant visualization and manipulative elements; (3) the interrelations need more explicit representations; (4) mismatches between science concepts and artificial concepts could cause confusion.

5.1.1. Likes: Children perceived analogical & embodied representations and their interrelations as effective scaffolding

Besides the embodied metaphors regarding physical space (e.g., flower–flower distance, pollen circle size), 16 students found the interrelations among analogies as helpful representations scaffolding them to recall and understand abstract AI concepts along with their interrelations. For example, the relationships among a pollinated flower, pollen, and beehive, which are honey bees pollinating a flower, and the flower's pollen getting collected into the beehive, are explicitly visualized in the analogical and embodied learning experience. This helped students understand that a user selects an item in a recommendation system, and then the user profile collects data on this user selection to represent the preferences of this target user.

5.1.2. Likes: Children enjoyed the vibrant representations and manipulative tools that concretize abstract math concepts

All the children enjoyed the exaggerated experience of standing in the clustered flowers that became increasingly similar, making the filter bubble effect more expressive and impressive. Students found that only by increasing flower diversity could they expand the flower-growing areas in the BeeTrap garden. This embodied experience stimulated students' urge to break the filter bubble clearly and engagingly.

Children perceived the withered flowers far away from the pollinated flowers as a powerful representation of the similarity-based ranking in content-based recommendation systems. Built upon this analogical representation, one student sketched their creative interpretation that the moving beehive is the power source for flowers to grow in the garden, which causes flowers far from the beehive to wither and die.

Children enjoyed roleplaying the analogical representations. Students annotated on existing designs that they liked roleplaying a bee and an environmental scientist. Bee is an analogy of the user of a recommendation system and environmental scientist is an analogy of an AI engineer developing a diversification algorithm. Children shared that such a combination of analogical representation of AI concepts and roleplaying created a motivating, goal-driven, and immersive learning experience.

5.1.3. Dislikes: Children requested more explicit representations of the interrelations among analogies and embodied metaphors

Ten participants pointed out that, while working on solving problems in BeeTrap, some of the interrelations between analogies or embodied metaphors were not explicit enough for them to immediately apply. For example, students mentioned that they did not instantly connect the flower bud, the authentic biology concept of what will grow into new flowers, with items that are candidates for recommendation. Some students did not successfully transfer the knowledge that physical distance in the garden represents the data similarity/distance to a more in-depth understanding that the bud-beehive distance represents the item–user distance.

5.1.4. Dislikes: Children perceived mismatches in the mixture of authentic science concepts and artificial concepts

Fourteen participants reported that the mixture of authentic and artificial concepts was inconsistent with the real-world science context, creating confusion that hindered their understanding of the corresponding AI concepts. For example, the relationship between the artificially moving beehive and the pollen circle, which is an artificial concept, confused some students. A beehive does not move based on the locations of the pollinated flowers in the real-world garden and there is no physical circle around a beehive. Some students mentioned that their observation of the beehive moving toward the pollinated flowers made them struggle to make sense of why the beehive was moving and how exactly the beehive's location was updated.

5.2. RQ2. What new analogical and embodied representations do children create through co-design and what are the underlying learners' needs?

This section introduces our findings that children's new designs (1) bridge the gaps caused by the mismatch between science concepts and AI concepts and (2) enhance collaboration and competition for gamification.

5.2.1. Bridging gaps in the embodied and analogical representations

First, children found a major gap lies between the artificial BeeTrap objects and the authentic science context. We identified seventeen design ideas replacing the BeeTrap representations that did not align with real-world gardens (Fig. 8). For example, eight new designs replaced the artificially moving beehive, such as (1) a honey pot holds pollen from the pollinated flowers (Fig. 8.1, 8.12); (2) a tree protects flower buds in a certain range so that the protected buds can grow (Fig. 8.5); (3) a tree holds the beehive with the branch; with different amounts of water that the tree gets, its branches get longer or shorter to move the beehive (Fig. 8.9, 8.10); (4) wind or a fan blows the pollen to change the range of growing new flowers (Fig. 8.12, 8.15); (5) a rain circle waters the flower buds to grow out (Fig. 8.9); (6) peer bees carry pollen from the pollinated flower and fly to the beehive, which explicitly represents the user profile's data collection process (Fig. 8.6); (7) a sun sheds light and provides energy for flower buds in a certain range to grow (Fig. 8.4); (8) a vase that can hold the pollinated flowers directly.

Second, children identified gaps in the learning content that lack explicit embodied or analogical representations. They creatively designed representations to concretize more nuanced AI sub-concepts underlying the existing AI concepts, such as in-depth mathematical concepts in a recommendation algorithm and breaking down "user profile update" into sub-concepts of "user selection", "data collection", etc. We identified seven ideas that serve this purpose. For instance, to demonstrate more details in the algorithmic step of deciding which items to recommend, children designed a sun to replace the beehive. The sun can provide different energy levels for buds to grow (Fig. 8.4). This representation embodies the concept of weights in an AI algorithm with different amounts of sunlight from the sun. Another example is that some children added lines between beehive and flower buds to visually represent and explain how flower buds get ranked by beehive-bud distance. This design reveals more mathematical details in the ranking formula. To step into one deeper layer of the diversification algorithm, children also created a set of garden tools, including shovels, sprinklers with different watering ranges, fertilizer, etc. These tools enable the environmental scientist to investigate how items are selected for recommendation and how to rank a specific type of items higher.

Third, another type of gap-bridging design enables players to switch between different spatial and temporal perspectives. This benefited exploring the garden and tinkering with the problems. For example, one participant added a time travel function for learners to re-visit gardens at different time points with different flowers alive. This design affords a more effective comparison of items that exist in a recommendation system and a more powerful interaction with the filter bubble formation. Students designed an option to observe the garden from a bird's view or zoom out the game map to inspect flowers from a third-person view (Fig. 8.11). This also makes the flower diversity changes in the garden more visible and concrete to children.

5.2.2. Support collaboration and competition for gamification

Following their interests, children helped with creating new social interaction elements for more child-centered gamification — what adult designers think is fun might not be fun enough for kids.

First, five distinct ideas were collected from children which introduce more BeeTrap elements supporting social interactions to make BeeTrap more engaging. Different roles of bees were proposed to map with either different AI functions or different stakeholders of an AI system. Children suggested roles beyond the bees that gather pollen, such as peer bees communicating information regarding the flower diversity (Fig. 8.8, 8.6), stay-home bees as data keepers, the protector bees who protect the beehive and flowers from the damage caused by AI ethical issues, queen bees as information collectors, worker bees using tools, and bad bees attempting to destroy the user profile (Fig. 8.3). One group added a bee shop to the game, for players to access different types of bees; different bees cost different number of flowers which is an incentive for boosting flower diversity (Fig. 8.13). Children also brainstormed ways to integrate more bee behaviors into the learning, such as bee dance and bee stinging (Fig. 8.7). In addition to adding different roles of bees, there was also an idea of having multiple scientists as the analogy for different AI engineers, who would communicate and collaborate to preserve the bio-diversity in the garden (Fig. 8.11).

Second, we identified five design ideas to enhance learners' motivation to level up in the activities. One group created an idea for learners

Fig. 8. New ideas co-designed by children: (1) the beehive is the power source; a honey pot carries nectar; (2) tree branches grow to collect data across different seasons; (3) different types of bees have different AI functions; (4) a sun recommends different items; (5) canopy covers a diversity range; (6) peer bees collaborate for diversification; (7) bees have different powers in the game; (8) peer bees communicate and pollinate flowers outside; (9) pollen clouds and rain circles grow flowers; (10) a tree moves the beehive; (11) add different scientists and a third-person view; (12) water drops grow flowers, wind blows pollen to farther flowers, and a pot collects honey; (13) a bee shop sells bees for different numbers of flowers, sprinklers reduce pollen and wind grows farther flowers; (14) game levels and stepping inside the beehive make the game more fun; (15) a flower locator locates flowers, a fan grows flowers, and jail represents the filter bubble; (16) overlaid circles compare diversity ranges.

to help bees escape a fly trap representing the filter bubble to level up (Fig. 8.7): "The fly trap can be a challenge. When a bee falls into the fly trap, we can take the challenge to save the bee out of the fly trap." Another idea also suggested introducing more levels of challenge in the game and embodying the challenge level with the size of the bee (Fig. 8.2): "Bigger bees face harder challenges."

Third, nine ideas were identified as representations to enrich the storytelling and roleplaying experiences with more toolkits contextualized in the garden and biodiversity context. Honey, water, and pollen buckets are added for the bees; bees have more storylines to conduct mini-tasks such as collecting pollen from a certain type of flowers. One group proposed the idea that the bee needs to fight against a fly trap to pass a game challenge; the bee has different storylines with multiple quests (Fig. 8.7).

5.3. RQ3. How does engaging as co-design partners impact children's learning experiences of target AI concepts and their potential to expand their understanding?

We identified three aspects of how co-design benefited students' AI learning: (1) transfer the knowledge into AI concepts beyond the original learning objectives; (2) enhance the learning of the target AI concepts; (3) get motivated to ask in-depth questions about AI.

5.3.1. Transfer the knowledge into more advanced AI concepts

New designs demonstrate students' understanding of more detailed or in-depth AI concepts beyond the scope of existing learning objectives: (1) collaborative filtering, (2) continuous output of the regression algorithm, (3) mathematical processes underlying data diversity, and (4) factors impacting AI recommendation performance.

For collaborative filtering, one new design added diverse types of bees as different users of the flower recommender. New flowers grow based on both the flowers pollinated by the target bee and bees similar to the target bee. This is aligned with the collaborative filtering technique in some AI recommendation systems, which ranks items based on both the user–item similarity and the user–user similarity.

For the regression algorithm's continuous output, one group used the analogy of "energy" to describe continuous value predicted by AI recommendation systems, moving beyond the simpler binary predictions of whether a flower bud would grow into a new flower in the current learning experience.

More tangible visual representations are designed for hidden mathematical processes of algorithms, such as ranking items based on their contribution to the data diversity among all the recommended items. One group visualized ranking algorithms by depicting connections between the beehive and buds with arrows and numerical values. This visualization aimed to clarify that rankings are determined by the data diversity of a group, represented by the total lengths of the connections between flowers.

Lastly, students added impact factors of the performance of AI recommendations, such as temporal and social interactions within the human–AI systems. They suggested using different seasons, where flowers bloom variably, as a metaphor for the evolving stages of AI recommendation systems. This idea was also extended to the social dynamics of bees, recommending the representation of social contexts in which AI systems operate.

5.3.2. *Enhance the learning of the target AI concepts*

We also observed how co-design processes enhanced students' grasp of the target AI concepts. *First*, five distinct design ideas replaced the pollen circle representing the ranking range in the recommendation algorithm. One group of children drew a tree in which the canopy size represents the data similarity/diversity range for ranking (Fig. 8.5). Players could manipulate the canopy size by watering the tree or removing the water. Flower buds within the shadow of the tree's canopy would grow into new flowers while the buds outside of the tree's shadow end up dying out. Other ideas included representing the ranking range by the size of rain circles or pollen clouds (Fig. 8.9, 8.10), watering pipes (Fig. 8.12), sunlight range (Fig. 8.4), etc.

Second, students created five new designs to represent user selection history and data collection in the user profile. For example, one group came up with the idea of using the sun to represent a user profile (Fig. 8.4). The user selection history documented in the user profile was embodied by the outer range of sunlight paths connecting with the pollinated flowers. Within the range of sunlight, buds were available to grow into new flowers, using the analogy of flowers receiving energy from the sun to grow.

Third, three ideas embodied the filter bubble consequences more explicitly. One idea was proposed to make the bee's strength or health vary based on the flower diversity they pollinate. If a bee does not gather pollen from diverse flowers to get enough nutrients, its strength would be downgraded, or else upgraded to become a stronger bee (Fig. 8.14). This embodied filter bubbles' ongoing impact on users of AI recommendation systems and strategies for how users can counteract filter bubbles' negative effects. Another group trapped the bee in jail to represent the filter bubble sequence (Fig. 8.15). It could motivate children to face challenges and strive to level up.

Fourth, three ideas revealed the mathematical concepts underlying the recommendation algorithm. One student overlaid two pollen circles, one large and one small, to help learners directly compare the outputs of a larger versus a smaller ranking list (Fig. 8.16). This design aimed to demonstrate the impact of specific steps in the diversification algorithm.

5.3.3. *Motivate students to ask in-depth questions about AI*

We observed that students' discussions during the co-design process demonstrated that such design practices motivate students to ask questions about more in-depth AI literacy that is not covered by the current AR learning experience, such as user diversity, more advanced data collection, and modeling in AI recommendation systems. Seven students asked for more details about the existing target AI concepts or discussed designs to convey those new AI concepts. One of them suggested designing a watering pot with different spouts to represent different ranking algorithms that decide which flower buds to grow. One student mentioned: "From step 1 'bee selects a flower to pollinate' to step 2 'the beehive holds the nectar of the selected flower', I am curious about what happens between the two steps. The current design only shows results but the process is unclear." Another student raised a question about how to grow new flowers outside of the pollen circle, behind which is how to generate new recommendations outside of the ranking range for diversity or similarity-based ranking algorithms.

6. Discussion

To create a child-centered AI learning experience, we co-designed with children from underrepresented backgrounds, building on the baseline design of BeeTrap. This study revealed children's preferences and ideas for embodied and analogical representations of AI concepts. We found that co-design practices can deepen children's understanding of abstract AI literacy by (1) enabling knowledge transfer to advanced AI concepts beyond existing learning experiences, (2) enhancing their grasp of the original target knowledge, and (3) encouraging students to ask insightful questions about AI. We derived design implications of using science concepts as analogies to teach children about AI concepts (Section 6.1), identified design goals to engage children as co-designers in analogical AI learning experiences (Section 6.2), and highlighted co-design's learning benefits (Section 6.3).

6.1. *Design implications of analogies from science contexts for AI concepts*

Our findings suggest K-12 science topics as effective sources of generating analogies to teach children about AI while the learning might be hindered by the relational patterns underlying complex science concepts.

K-12 science topics as effective analogies for AI concepts. Building on prior work (Gentner et al., 2004; Nokes and Belenky, 2011), we found that analogies based on familiar science contexts effectively bridge the understanding of AI concepts. By mapping familiar scientific ideas to new AI concepts, these analogies support students' conceptual change (Clement, 2013). Analogies typically involve two types of similarities between the base and target domains: surface features, such as color or shape, and deep structural properties (Gentner et al., 2003). BeeTrap analogies were specifically designed to emphasize structural similarity, which involves shared patterns of relationships among constituent elements (Duit et al., 2001). For instance, the analogical relationship between a pollinated flower, pollen, and beehive helped students grasp the abstract concept of data collection in recommendation systems. The visualization of a bee pollinating a flower and the subsequent collection of pollen into the beehive resonated with students, allowing them to draw parallels between this process and how user preferences are recorded and used in AI-driven recommendations. The reasoning process aligns with analogical learning in which learners identify similar relational patterns in both the base and target domains and map correspondences between entities in both domains based on their relational roles (Lu et al., 2019).

Familiar ethical concepts in K-12 STEM subjects could be a common ground for students with limited access to AI technologies to understand AI ethical issues. For example, **biodiversity**, emphasizing the necessity for bees to have diverse flowers to maintain their health overall, was a powerful analogy to illustrate the importance of diversification in recommendation systems. This concept fostered students' critical thinking that, much like a bee's need for a variety of flowers, we as consumers of recommendation systems also need diverse content.

Challenges in identifying relational patterns. However, the findings also indicate that the relational patterns embedded within these analogies and metaphors were not always immediately apparent to the children. For example, a flower bud, representing potential items for recommendation, did not always translate effectively into the students' understanding. The physical distance in the garden, meant to symbolize data similarity or distance, was another concept that some students struggled to fully comprehend, particularly in terms of its representation of item–user distance. This is a known challenge in analogical learning due to its context sensitivity and student expertise gap (Hajian, 2018). Even with careful planning, students may fail to notice the intended relational similarity (Harrison and Treagust, 2006). The mixture of authentic biological concepts with artificial elements also posed challenges. The artificial concept of a moving beehive, which does not align with real-world behavior, confused several participants. It is challenging and often impossible to find a source analog that perfectly maps every relation in the target concept (Dai et al., 2024).

6.2. Design opportunities to involve children as co-designers

Our findings identify three design opportunities for engaging children as co-designers of analogical AI learning experiences: (1) authentic analogies drawn from science contexts, (2) metaphoric representations that bridge the gap between science and AI concepts, and (3) elements that incorporate gamified learning experiences.

Authentic analogies with higher degree of shared structure and relational role. Children consistently highlighted the need for analogies that closely mirror the patterns of reasoning found in the natural world, as these more authentic analogies facilitate easier transfer of knowledge and more effective analogical reasoning. For instance, many students recognized the disconnect between the artificial elements in BeeTrap, such as the moving beehive, and real-world garden behavior. This recognition led to numerous design ideas aimed at replacing or refining these representations to better align with actual scientific principles. Examples include the bee carrying pollen and flying to the beehive. These child-generated designs demonstrate a strong preference for analogies that maintain a higher degree of fidelity to real-world science and that share similar relational roles in reasoning. Understanding why the base entity behaves as it does and then transferring that knowledge to the target is crucial for learning through analogy (Gray and Holyoak, 2021). This aligns with research suggesting that the key to effective analogical reasoning lies in identifying similar relational roles between the base and target domains, rather than focusing on direct similarities between individual entities (Lu et al., 2019).

Metaphoric representations bridge the gaps in analogies. To address gaps where direct analogies may fall short, children created metaphoric representations that bridge these gaps. Recognizing that certain analogies, such as the moving beehive, did not fully align with real-world behavior, students sought to create metaphors that would offer a more intuitive learning experience. For example, one group reinterpreted the concept of the pollen circle as "energy", a metaphor that helped them understand how AI algorithms might assign different weights to data points, leading to more nuanced recommendations. Students introduced visual elements such as numerical values and connections between the beehive and flower buds to make sense of the ranking process in AI systems. This extends the finding from existing research that novice adults can intuitively understand recommendation algorithms through metaphoric representations (Alvarado et al., 2021). This also links to extensive research on the learning benefit of storytelling (Alterio and McDrury, 2003) that constructing understanding by connecting with prior experience and knowledge can effectively enhance learning (Mussen et al., 1983).

Engaging gaming elements. Children's feedback and design ideas also emphasized the value of incorporating gamification elements for more dynamic and interactive learning environments. Children suggested introducing various roles within the game, such as stay-home bees as data keepers or protector bees guarding against ethical issues, which could serve as analogies for different components or stakeholders in an AI system.

Furthermore, the idea of incorporating levels of challenge, such as helping bees escape from a fly trap or facing more difficult tasks as a larger bee. The challenge of an educational game corresponding to the learner's skills could lead to a flow state in which the learner is highly concentrated and experiences the learning activity as intrinsically rewarding (Oksanen, 2013).

Integrating enriched storytelling was another key strategy students used for improvement. By adding more contextually relevant toolkits, such as honey or pollen buckets, and creating mini-tasks for the bees, the children envisioned a more immersive and motivating educational game.

6.3. Exploring co-design as a form of learning

Employing analogy for learning AI concepts is a niche area, and hence children's insights are valuable to inform and further improve the learning design. However, co-design or participatory design with children goes beyond merely involving children in the design process and focuses on what designers can learn from participants. It encompasses a set of methods and practices that scaffold the design experience, encouraging children to reflect on their existing knowledge and build upon it (DiSalvo, 2016). In exploring co-design through a learning lens, it comes to light that co-design activities provide a rich environment for children to understand what knowledge they have grasped, generate analogical inferences, and collaboratively construct new knowledge in new ways.

Through these activities, students were no longer passive recipients of information but active participants in the learning process, which deepened their understanding of the AI recommendation system. One of the key indicators of this enhanced understanding was the students' ability to transfer knowledge gained during the activities to more advanced AI concepts. For example, students demonstrated their grasp of collaborative filtering by creating designs that mirrored user–item and user–user similarity, a concept that extends beyond the simpler models they were initially taught. Similarly, the introduction of "energy" as an analogy for continuous values predicted by AI systems shows a sophisticated understanding of how AI recommendations can go beyond binary predictions. It resonates with the research that engaging children in co-designing their learning environment could help them develop a deeper understanding of abstract concepts and translate this theoretical knowledge into tangible solutions (Famaye et al., 2024).

Moreover, the creation of tangible visual representations of hidden mathematical processes within AI algorithms, such as using arrows and numerical values to depict data diversity in ranking algorithms, further illustrates the depth of understanding achieved through these co-design activities. Students also proposed innovative ideas, such as using seasons to metaphorically represent the evolving stages of AI recommendation systems and incorporating social dynamics into their designs. This aligns with research that children generating solutions to distant analogies selectively show their continuous attention to relational information (Gray and Holyoak, 2021). This generation effect could lead to better retention than passively viewing and evaluating completed analogies (Metcalfe and Kornell, 2007). The co-design process not only deepened understanding but also encouraged further question-asking about AI literacy. The collaborative co-designing fostered a sense of inquiry among students, leading them to ask questions and explore concepts beyond the scope of the current learning experience. For instance, students expressed curiosity about the detailed processes underlying AI recommendation systems, such as the steps between a bee selecting a flower and the beehive storing pollens, or the mechanisms for generating new recommendations outside of a predefined ranking range. These questions and discussions highlight the students' growing interest in the intricacies of AI and their desire to delve deeper into the subject.

7. Limitations and future work

There are a few major limitations of this work, including the analogy design in BeeTrap, the limited number of participants, and the unexpected study setup changes caused by the summer camp's nature of flexibility. *First*, as reported in Sections 5.1.4 and 5.2.1, gaps exist between real-world bee pollination and AI recommendation mechanism. To bridge the gap, our design involves a few artificial objects (e.g., the beehive that moves to the pollinated flowers) which break the scientific facts. Although these analogies have been confirmed and some of them are designed by a few in-service K-12 science teachers, and findings do not indicate their harm in learning, we still consider them as a limitation in our design and plan to improve them in future design iterations. *Second*, with 11 high school students and nine middle school students from two summer camps voluntarily signed up to participate in the study, our sample size is too limited to conduct more statistical analysis. *Third*, student attendance in a summer camp is relatively less controllable. We had to adjust the grouping for three activities based on the students who showed up on the day, and this is the reason that the grouping for the diversification activity is different from the first two activities. Moreover, an unexpected occupation of the study site made s2p1 wait for a long time before she could play with the diversification activity. Such unavoidable disruption in the study may influence s2p1's interest and engagement with the learning experience.

Beyond the current scope, we have not investigated the unique learning benefits of different design dimensions: (1) AR versus non-AR, (2) embodied versus non-embodied, and (3) analogical versus non-analogical. Future work could also validate the co-design outcomes with a broader audience. We can observe children's learning behaviors when multiple analogies and embodied metaphors are provided to represent the same AI concept. With the fast advances in generative AI (GAI), another promising research direction is to explore how GAI can support children's co-design for AI literacy.

8. Conclusion

This study focused on co-designing embodied and analogical learning experiences with children using an AR application to teach AI concepts related to the filter bubble's impact, mechanisms, and mitigation strategies. BeeTrap was used as the baseline design for engaging children as co-designers. By empowering children in the design process, the study enhanced the child-centered AI learning experience. Findings revealed that children identified gaps in analogy and metaphor design, highlighting the need for explicit representation of underlying AI sub-concepts. They also developed new designs to address mismatches between the source and target domains. Through co-design practices, children achieved a deeper understanding of abstract AI concepts and demonstrated the ability to transfer their knowledge to more advanced aspects of AI literacy.

CRediT authorship contribution statement

Xiaofei Zhou: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yunfan Gong:** Investigation, Formal analysis, Data curation. **Yushan Zhou:** Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yufei Jiang:** Formal analysis. **Zhen Bai:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zhen Bai reports financial support was provided by National Science Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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