Approaching “Filter Bubble” in Recommendation Systems: A Transformative AI Literacy Learning Experience

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Abstract: Young learners today are constantly influenced by AI recommendations, from media choices to social connections. The resulting "filter bubble" can limit their exposure to diverse perspectives, which is especially problematic when they are not aware this manipulation is happening or why. To address the need to support youth AI literacy, we developed "BeeTrap", a mobile Augmented Reality (AR) learning game designed to enlighten young learners about the mechanisms and the ethical issue of recommendation systems. Transformative Experience model was integrated into learning activities design, focusing on making AI concepts relevant to students’ daily experiences, facilitating a new understanding of their digital world, and modeling real-life applications. Our pilot study with middle schoolers in a community-based program primarily investigated how transformative structured AI learning activities affected students’ understanding of recommendation systems and their overall conceptual, emotional, and behavioral changes toward AI.

Introduction

Artificial Intelligence (AI) recommendations influence many of our daily decisions, and this extends to the younger generation who receive recommendations from videos suggestions, friendship on social media, to education and career opportunities. While the ease of finding information tailored to an individual’s preferences can lead to the “filter bubble” effect, it might also limit people’s exposure to diverse options and opinions (Gao et al., 2022). Young learners, who are still developing their understanding of AI and critical thinking, might be more vulnerable to filter bubbles.

Recognizing this, we introduce "BeeTrap", an embodied Augmented Reality (AR) learning game focused on mechanisms and ethical aspects of recommendation systems. BeeTrap is more than just an interactive game; it’s designed as a bridge for transformative AI education, aiming to take young learners beyond mere awareness of the filter bubble effect and to equip them with the skills to deconstruct and understand the mechanisms behind recommendation systems. Through this embodied experience, we hope to not only demystify AI for young learners but also develop their sense of agency- to challenge the deep-seated assumptions that shape their perspectives towards AI and act on new understandings. We piloted this learning game over a four-day summer camp with middle school students in a community-based program, evaluating how the game reshapes perceptions, fosters critical consciousness, and encourages proactive engagement with AI. This paper intends to address the following two questions: (1) Did transformative design of activities support students’ conceptual understanding of recommendation systems? (2) How did transformative design of activities impact students’ learning experience of AI and recommendation systems?

Towards designing a transformative experience of AI literacy learning

Learning ethical aspects of AI in K-12 context

Children’s increasing contact with AI technologies in daily life, such as AI recommendation systems in social media, calls for preparing the young generation with literacy around AI ethics issues (Zhang et al., 2022). Furthermore, daily life AI technologies with real-world dilemmas provide a design space for learning experiences with sustainable engagement and ethical reflection (Schaper et al., 2023). Existing research have investigated if children can understand different values of various stakeholders of AI technologies (DiPaola et al., 2020) and the underlying datafication process (Wang et al., 2023). Such perspective-changing learning experiences support students to reflect from multiple AI stakeholders’ perspectives and empower them to transform beyond AI users. Researchers have also explored how immersive experiences could foster youth to think critically about contradictory options on the ethical aspects of AI technologies, such as the trade-off between the technology's convenience and the loss of identity (Lee et al., 2023).

Transformative experience and conceptual change

When students apply what they've learned in schools to see and experience the world differently in their everyday lives, this encounter can be considered a transformative experience (TE) (Pugh, 2002). In this case, transformative refers to the application of learning content to everyday life in ways that result in thinking about aspects of the digitalized world in meaningful and new ways, attending to unquestioned assumptions, and exploring the impact that new insight can make on their own lives, their community, and society (Pugh et al., 2010).

TE model has proven effective at fostering transformative experiences within pedagogical contexts. Research by Pugh (2002) and Girod et al. (2003) incorporated elements of the TE model for high school biology and elementary-level earth science curricula. Both researchers found that this model was more effective at fostering transformative experiences than other instructional conditions. Furthermore, the TE model also supports conceptual understanding. For example, in a study of students' understandings of natural selection, Pugh (2002) found that students receiving the TE intervention maintained their level of understanding of the content over time, while students receiving inquiry-oriented instruction reverted to prior misconceptions.

Many of the AI learning experiences are designed to impart concepts, and principles or to teach new information. Less common are experiences designed to transform the way learners perceive and experience the world (Lee & Hu-Au, 2021). AI literacy education should open thinking for new ways of being in the world, not merely acquiring technical knowledge and skills. We therefore considered how AI literacy learning might highlight students' subjectivity and enable them to develop their relationships with the AI-infused world. To design a transformative experience related to AI literacy, we followed Pugh and colleagues' (2010) model of teaching for transformative experiences in science that included three components: (1) reframing the content as relevant to daily life; (2) scaffolding re-seeing and (3) modeling re-enacting.

Reframing the content prepares learners for the possibility that their perception of the world may change as they explore new ideas. It involves identifying an important AI concept and connecting it to familiar, everyday experiences. Tension may arise as learners' existing frames of reference are identified as potentially problematic (Dewey, 1993). This tension is pertinent in learning AI and its ethical implications, as learners often encounter AI in daily life without realizing its presence or recognizing the ethical issues it entails. Thus, it could motivate learners to search for new ways of thinking.

Scaffolding re-seeing refers to providing guidance to help learners see the aspects of the concept in new ways. A re-seeing activity encourages learners to pursue deeper layers of meaning and helps them develop their cognitive capacity to transfer their learning to a novel context (Girod et al., 2003).

Modeling re-enacting aims to integrate the learning of the first two phases. This phase presents the real-world issue and prompts learners to consider how to approach the challenge and make an impact, thereby bringing them greater meaning and excitement. TE model assumes that learners are unlikely to actively engage in transfer in their everyday experience unless all three phases are integrated into instruction (Pugh et al., 2010).

BeeTrap instructional design

Inspired by the transformative experience (TE) model, we aim to nurture a shift in learners' perception of recommendation systems through stages of reframing, re-seeing, and re-enacting. In the following sections, we introduce the learning objectives and instructional design for three BeeTrap activities: (1) Exploring the filter bubble effect (2) Recommendation systems mechanism (3) Diversification to break the filter bubble (see Table 1).

In the *first learning activity*, we tackle the concept of "filter bubble", a phenomenon where recommendation systems narrow down content based on past choices, leading to diminishing content diversity (Gao et al., 2022). The goal is to have learners grasp its significance by directly observing its effects. As learners step into this garden using a tablet, they take on the role of "bees" with a mission: reduce a flower diversity score displayed on their screens (Fig. 1(1)). Each flower in this garden carries distinct attributes including color, petal size, and shape, representing the multifaceted nature of content in recommendation systems. Acting as bees, learners decide which flowers to pollinate, effectively making 'choices'. Over time, learners observe the formation of filter bubbles in the garden, with flowers similar to what they have pollinated growing and others withering away (Fig. 1(4)). Such experience aligns the abstract concept of filter bubbles with a tangible, daily-life experience. Through this reframing, we aim to deepen learners' personal connections with the ethical challenges of recommendation systems, setting the stage for more in-depth exploration in subsequent activities.

The *second learning activity* delves into the mechanisms of content-based recommendation systems, which generate recommendations based on items selected by the user previously (Aggarwal., 2016). As learners navigate the garden, each interaction serves as a metaphorical step in understanding how digital platforms curate content for users. Pollinating different flowers mirrors data collection, and the central beehive symbolizes how user profile changes to depict user's preference (Fig. 1(2)). The numbered buds on the ground indicate how items for recommendation are ranked. The top-recommended buds grow into new flowers, like how platforms suggest content for users (Fig. 1(3)). Learners go through four rounds of pollination in the virtual garden. In the first two rounds, they are guided to observe and share their findings of garden change. In the subsequent two rounds, learners answer on-screen multiple-choice questions that prompt them to reflect on their interaction: (1) What goes into the beehive? (2) What do the flower buds on the ground represent? (3) What do numbers above the flower buds represent? (4) What does the pollen circle represent? (5) How are the flowers located in the garden? The second learning activity demystifies the inner workings of recommendation systems and scaffolds learners' "re-seeing" of the invisible algorithms that shape their digital experience. It nudges learners to reconsider the digital content they encounter every day.

In the *third learning activity*, learners get hands-on experience in tackling the filter bubble issue observed in the first learning activity. We equip learners with two main tools to simulate a two-step diversification algorithm: a pollen circle to enlarge the diversity range of items to be ranked (Fig. 2(1)) and a toggle button to decide to rank items for recommendation either by similarity or by diversity (Fig. 2(2)).While doing these tasks, learners switch between two roles: one as a "bee" looking for diverse flowers to pollinate, and the other as an "environmental scientist" trying to make the garden as diverse as possible. When roleplaying as the scientist, learners manipulate the pollen circle size and control the toggle button for flower growth pattern. As they make decisions and pollinate flowers, the garden changes in real time. The third learning activity embodies the "modeling re-enacting" stage of TE by immersing learners in hands-on experimentation to solve real-world challenges of the filter bubble. They not only learn how to diversify recommendation systems but also learn, in a hands-on way, how their choices can make a difference. The specific details of system design can be found in another study of this research project (Zhou et al., in press).

Table 1
BeeTrap learning design

Level	Topic	AI learning goal
Re-framing	Filter bubble effect	Understand the definition of filter bubble: an ethical issue in recommendation systems where users continually receive similar content based on past choices. Recognize the effect of decreasing content diversity and increasingly restricted user choices.
Re-seeing	Content-based recommendation systems mechanism	Understand the algorithmic steps of content-based recommendation systems: (1) a user selects an item (2) record the item in a user profile describing the user's interests (3) compute the similarity between the user profile and all available items for recommendation (4) rank all available items based on the similarity to the user profile (5) recommend the top N items in the ranked item list.
Re-enacting	Diversification Algorithm	Apply diversification algorithm: (1) tune parameters for ranking (2) switch between similarity-based ranking and diversity-based ranking

Methods

Participants

The participant group for the study consisted of nine students in a community-based program. The individuals spanned a range of grade levels from 6th to 10th, with one individual's grade unspecified. A majority of the participants identified as Black or African American, while some reported being of biracial background. Gender representation in the study was almost equally distributed, including five females and four males (see Table 2).

Table 2
Demographic information of participants

ID	Gender	Grade	Race
P1	Female	8th	Black or African American
P2	Male	7th	Black or African American
P3	Male	7th	Black or African American
P4	Female	8th	Black or African American
P5	Female	8th	White+Black

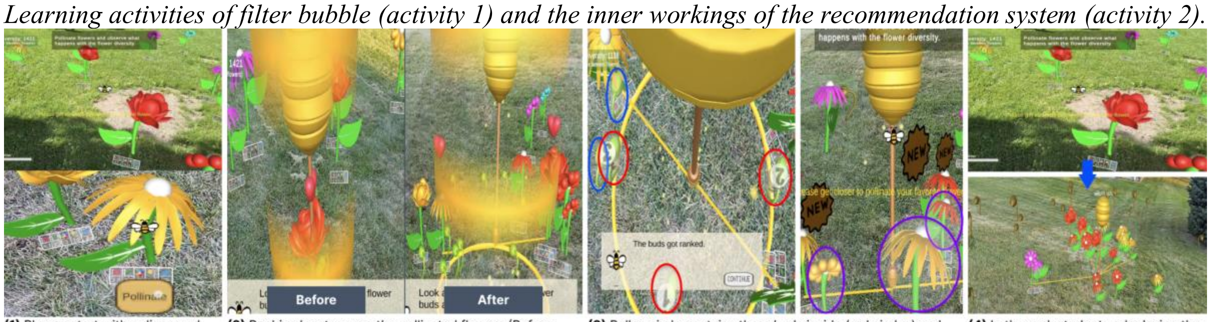
P6	Female	6th	Asian+Black
P7	Male	8th	White+Black
P8	Male	10th	Black or African American
P9	Male	NA	Black

Study procedure

The study was conducted on-site in a classroom during a summer camp. Before the study, each participant was informed about the study procedure and signed an assent form. Each participant went through three BeeTrap activities without instructions. Two researchers resided in the same room throughout the entire study session to assist the participants with the study procedure when requested. The entire study lasted 2 to 2.5 hours per participant and was carried out in four consecutive days. A warm-up activity about AI was given at the beginning.

Figure 1

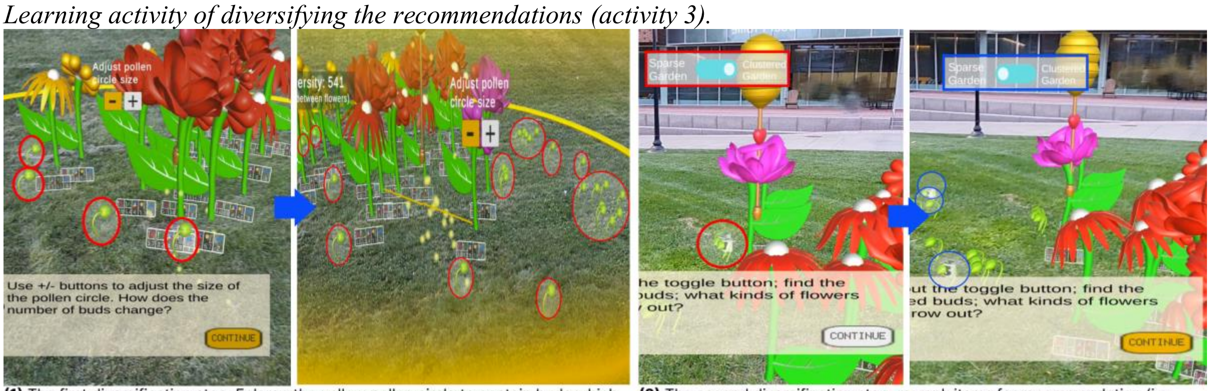
Learning activities of filter bubble (activity 1) and the inner workings of the recommendation system (activity 2).



(1) Players start with a dispersed garden with diverse flowers and pollinate a flower (yellow daisy). **(2)** Beehive locates near the pollinated flowers (Before: above the first pollinated red rose. After: moves between the newly pollinated yellow daisy and the red rose. **(3)** Pollen circle contains three buds inside (red circles) and some buds outside (blue circles). Buds closer to the beehive get higher rankings and grow into new flowers (purple circles). **(4)** In the end, students roleplaying the bee are trapped in clusters of similar flowers. The filter bubble is formed.

Figure 2

Learning activity of diversifying the recommendations (activity 3).



(1) The first diversification step: Enlarge the yellow pollen circle to contain buds which can grow into more diverse flowers; more buds are included for further ranking. **(2)** The second diversification step: re-rank items for recommendation (i.e., buds) based on diversity (blue circle) rather than similarity (red circle).

Data collection and data analysis

Before the experiment sessions, participants took the pre-test (including multiple-choice questions and open-ended questions) adapted from previous literature (Agarwal, 2013; Gao et al., 2022; Nguyen et al., 2014). The questions were designed to align with the specific learning goals of each activity. After each gameplay session, participants took the corresponding post-test. The pre-and post-tests were verified and validated by AI experts to ensure their measurement validities.

Following each session, participants participated in a reflective discussion. Prompts were given to guide them connecting the AI concept with their daily experience. At the end of the three sessions, a final semi-structured interview was conducted to ask about their overall experiences and their future use of AI and recommendation systems. All were audio-recorded under consent and were then automatically transcribed through Rev (rev.com).

For pre-posttests, two researchers graded the responses separately. The process's reliability was affirmed with Cohen's Kappa scores of 0.78. A descriptive analysis and paired t-test were conducted to measure learning gains. For discussion and interview recordings, thematic analysis was conducted to identify themes related to our second research question (Brauna & Clarke, 2006). The initial open coding phase was conducted by the two authors to identify participants' transformative experiences in response to different activities and discussion prompts. It was conducted individually at first and then reviewed together to search for themes. The themes were then reviewed and refined by all authors to create an overall understanding of the data. Compelling extracts were chosen from the data to illustrate and support findings.

Results

RQ1: student's learning gains on the conceptual understanding

The paired t-test results of pre-posttest suggest that the AR learning activities significantly supported students' conceptual understanding of most aspects of recommendation systems (see Table 3). The improvement was evident in almost all the topics assessed, except the basic algorithm for diversification, where the change was not as statistically significant.

Table 3

Pair sample t-test of students' conceptual understanding of recommendation systems

Target concept	Pretest		Posttest		Pre-post		
	M	***SD***	***M***	***SD***	***Mean Difference***	***SD***	***Sig (1-tailed)***
Recognize AI recommendation systems in daily life	.44	.88	2.78	.44	2.33	1.12	<.001
Filter bubble definition and impact	0	0	2	.87	2	.87	<.001
User profile	0	0	2.11	.96	2.11	.96	<.001
Data similarity computation	.78	1.30	2.33	1.32	1.56	1.51	.007
Basic algorithmic steps of recommendation system	.22	.67	2.44	.73	2.22	1.09	<.001
Basic algorithmic steps for diversification	1	.87	1.89	1.36	.89	1.69	.077
Overall average	.41	.43	2.26	.34	1.85	.59	<.001

RQ2: students' transformative experience of AI and recommendation systems

Learning AI through embodied experiences supports students' conceptual understanding

Immersive visualization made the abstract concept of "filter bubble" easier for students to grasp and supported the reflection of the impact. The visual of flowers grouping together in the virtual garden made it obvious to students to connect with the loss of diversity and supported them to reflect more on why diversity is needed in AI recommendation systems. P3 described his experience of walking in the virtual garden with fewer and fewer areas with flowers: "In the beginning, it (flower) was like spaced out. You had to walk more to see. You have more space to explore... Cause if I just like one flower, it'd be all clustered up. You're not gonna go elsewhere if all flowers clustered up. (I realize) don't stay on one thing for too long."

The AR environment guided students' attention to critical components. Visual cues ensured students focus on key garden objects. Scaffolded multiple-choice questions were integrated to lead students to understand how recommendation systems work. In post-activity reflections, students showed their understanding of recommendation systems mechanism using the garden metaphors. For instance, p8 explained: "When I pollinate certain type of flowers to grow, the beehive moves with me. And then it grows more buds, which grow into that flower that you just pollinated. So eventually the diversity will get smaller and only that specific flower will only be there. Like YouTube, those flowers are content."

In the third activity, students played with virtual objects to conduct hands-on trials of diversification algorithm. Students experimented with different choices and directly observe the effects. All students successfully increased the flower diversity of the garden to the target score. Students' reflections also show that the direct manipulation supported them in illustrating the detailed algorithmic steps for diversification. P2 mentioned: "I used the tool to expand the circle. Enlarge the options to recommend and then recommend the most diverse one to bee."

Agency in transfer: making changes towards self and beyond

Our study shows the transformative potential of understanding the mechanisms and diversification algorithms in that students could critically interpret the content they consume, make ethical choices, and find ways to see more diverse content, even when algorithms suggest otherwise.

Almost all students indicated an enhanced awareness of the filter bubble phenomenon and its inherent challenges. For example, P2 mentioned, “If I’m playing like one game and if I played a lot, then that game will recommend more games that are similar to that game. So the diversity would be smaller.” This comment not only shows an understanding of the recommendation's mechanisms but also illuminates the consequential limitation in content diversity. Learning inner workings also nurtured a more critical approach to content consumption, P3 shared, “I’m gonna follow some parts, but not all parts. I’m gonna try to get creative with it.” Similarly, P5 noticed that after playing BeeTrap, it’s easier for him to know when computers are making suggestions. He also pointed out the importance of having independent thoughts and identified the risks of relying too much on what AI recommends. When asked about how they would use recommendation systems in the future, P2 said, “I think I wouldn’t always follow what they suggest. Like when I’m watching a video, I watch what I wanna watch... I try to search for something new that I am interested in learning more.” Likewise, p6 illustrated an evolved understanding of the recommendation systems and the importance of seeking diverse content, “I didn’t realize that it is a recommendation system, like TikTok and Instagram. But now I realize that in the entire world, there are much more videos, much more music, much more youtubers than we can see. In the future, I think I’m going to have different ideas about what I want to watch. Not just like the same videos over and over and over.”

Students show motivation to inform people around them of ethical considerations of recommendation systems. For instance, P7 compared AI recommendation systems as brain, and he would want to “tell them (family and friends) how this brain works so they can follow in order to make right choices”. P2 planned to explain to his younger cousin how YouTube keeps suggesting his favorite videos like "Coco melon", “It’s challenging to explain. But I am thinking I am going to tell him that YouTube knows that you like Coco Melon and then it gives you a lot of Coco Melon. And you might not see other videos very often.” Their intent to share this newfound comprehension with family and friends highlights the development of agency in extending knowledge from the individual to the community. This resonated with P4 as well, who noticed that not everyone in her community knows about the "filter bubble" or how recommendations work. So, she planned to make a slide show to explain these concepts to them. Furthermore, she also hoped to inspire community members to break the filter bubble and consume recommendations more critically, “People might say ‘I’ll just take whatever my Instagram shows me, or I would just watch whatever my YouTube gave to me.’ I will tell them that AI would recommend the stuff that you would usually watch. You should try something new, so you won't be watching or hearing the same thing over and over. It will be more diverse. And you will see more diverse opinions as well.”

Learning about how recommendation systems work and how to diversify recommendations do more than just enlighten learners; they inspire innovation. One student (P1) shared, “If I do become invested in AI, I could use the recommendation (algorithm) to create an app similar to TikTok or something like that, but I will try to avoid the filter bubble issue, as we do (diversify recommendations) in the game.” This shows that the activities have the potential to motivate learners to think of AI’s ethical implementation for the greater societal good.

The activities created a transformative experience and cultivated students’ agency throughout the learning process, pushing them to go beyond just understanding 'how' things work. They also prompt students to ask 'why' and consider 'for whom' when thinking about future possible AI design.

Attitudes shift and future imagined use of AI

Before engaging in the learning sessions, a majority of students either possessed negative or relatively indifferent attitudes toward AI. Their perspectives ranged from limited understanding to fear for its impact on humanity. However, after the learning activities, a notable transformation in attitudes and motivation has been observed. For instance, p1’s early exposure to AI was fragmented and superficial, mainly through platforms like TikTok. After the activities, P1 articulated a deeper appreciation towards learning the inner workings of recommendation systems, saying, “I now know how they (recommendation system) know what I like to watch. It’s pretty cool because I now understand more. And AI seems a cool topic to learn about if I can know more about it.” This shows P1’s continuous interest and motivation to investigate more about AI, which also resonates with other students’ experiences. For P3 and P7, at first, they thought AI was a distant concept from their daily experiences and didn’t really care for AI. But after activities, they said they could recognize recommendation systems in their daily life, such as some social media platforms, and recognize AI’s prevalent role in everyone’s life. The most dramatic shift was observed in P5, who once held fears of AI overpowering human creativity and even leading to humanity decline and now gave away to a more optimistic view. After the activities, he stated, “I understand AI (recommendation system) more now, like how it works…I feel it could be beneficial only if we use it right. I feel like I can probably design a better recommendation system.”

Beyond attitude shifts, the activities also sparked students' imaginative considerations of how they could integrate AI into their personal passions and interests in the future, though they might not envision themselves primarily as AI engineers. P7 described a scenario of AI's potential intersection with sports, "I am interested in sports. But I think I can use AI to help me. Like when you are playing basketball, AI can tell you where your points are, what your heart rate is, how many calories you burn, what's the speed of the ball. And then you shoot, AI can tell how likely you gonna miss it." Similarly, P4, who wanted to be an entrepreneur, recognized AI's capabilities of finding targeted customers for her. P6, with aspirations in law, viewed AI as a valuable assistant but emphasized the importance of personal judgment, asserting, "I think for legal stuff, I can always ask AI questions. But I think I should have my own opinion. I won't have to use AI, rely on it all the time for things that I know how to do."

These reflections highlight a critical outcome of the learning activities, which could serve as a transformative platform where students not only expanded perspectives on AI but also internalized its significance. They began to imagine varied and creative applications that align with their personal aspirations and values. Students became more aware of the balance between AI and human agency.

Discussions

The findings from this study demonstrate the transformative potential of learning experiences designed to scaffold young learners' understandings of and agency with AI. Our findings show that BeeTrap supported young learners' critical reflection about recommendation systems and their societal implications, and empowered them to become informed users and likely change-makers in a digitized society.

Students were first immersed in an environment where they saw the real-time impact of their choices. As they saw the garden change based on their decisions, they could see firsthand how algorithms can shape and limit what they see and understand. This experience made them more aware of AI's ethical aspects. They began to see the links between recommendation systems and their everyday experiences. More importantly, they came to understand that AI is not perfect. It can have biases and can limit their exposure to a broader worldview.

Young learners come across AI every day. Many of them are unaware of its existence or view AI as a mysterious and even intimidating entity (Szczuka et al., 2022). By delving into how AI, particularly recommendation systems, operates, this "mystery" becomes clearer. They came to understand that AI's actions stem from data and specific algorithms. As highlighted by Touretzky et al. (2019), AI literacy education should help students understand that AI is a sensory technology, which uses data to improve its functionality. Gaining insight into how AI works can decrease intimidating feelings and can ignite curiosity to delve deeper. Students' hands-on interactions that shifted diversification algorithms as they influenced the garden's diversity gave students practical experience in steering AI results. This involvement not only further clarified AI's inner workings but also boosted their confidence about harnessing AI's potential in the future. Such an approach is in line with Schaper et al.'s (2023) assertion that equipping young learners with AI tools can inspire responsible behaviors and nurture active digital citizenship.

After students understand the ethical challenges, the mechanics behind AI, and how to diversify recommendations, they transition from being passive consumers to informed users, and potential future innovators. Empowered with this knowledge, they were positioned to not only question AI decisions but to inform community members and conceptualize improved recommendation systems. This learning process highlights growth in their sense of agency- transforming from personal change to influencing broader societal changes. Transformative AI learning design could nurture a proactive application of their learning beyond just the classroom.

Furthermore, Transformative AI learning design has the potential to reshape students' attitudes towards AI from negative or indifferent to positive. Research also shows that uncovering the AI black box helps young learners develop a more optimistic attitude towards AI (Kajiwara et al., 2023). Interestingly, while envisioning their AI-infused future, most did not see themselves as direct AI specialists. Instead, they imagined blending AI into their fields of interest. It shows the emphasis they placed on human creativity and decision-making, even in an AI-driven environment. By dispelling the myths around AI and encouraging a new perspective, we equipped learners for a future where they might collaborate with AI. This approach cultivated a mindset where AI is seen as a versatile tool- a creation they can mold and influence, not an unchallengeable force to be passively accepted.

By encouraging learners to explore and reinterpret AI, our design fostered cognitive, affective, and behavioral shifts towards AI. Further research is needed to understand which design element specifically triggered these changes. It is also crucial to assess if this transformative experience holds a lasting influence beyond the initial learning experience. Students sometimes found it hard to link the garden stories to AI terms. Future research in AI education could consider facilitating these connections by seeking more effective ways to bridge these conceptual gaps.

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