OptiDot: An Optical Interface for Children to Explore Dot Product and AI Recommendation

Xiaofei Zhou
xzhou50@ur.rochester.edu
University of Rochester
Rochester, New York, USA

Pei Xiong
pxiong5@ur.rochester.edu
University of Rochester
Rochester, New York, USA

Qinqin Xiao
qxiao5@u.rochester.edu
University of Rochester
Rochester, New York, USA

Zhen Bai
zbai@cs.rochester.edu
University of Rochester
Rochester, New York, USA

ABSTRACT

Understanding the inner workings of Artificial Intelligence (AI) recommendation systems may benefit children in becoming more sensible consumers of the ever-growing information in their daily lives. It may further enable deeper reflections on related ethical issues such as the filter bubble. With limited prior knowledge in math and computing, children often find AI concepts overly abstract. Inspired by optical computation, we propose a novel tangible interface, OptiDot. Through exploratory manipulation with light beams, OptiDot supports children in learning the dot product—a building block for numerous AI algorithms—and AI recommendations through embodied learning experiences. Findings of a preliminary user study with ten middle school students indicate the effectiveness of the key embodied metaphors. We also discuss the design implications and challenges of developing optical-inspired learning tools for children.

CCS CONCEPTS

• **Applied computing → Interactive learning environments**; • **Social and professional topics → Computing education**; • **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

Tangible interface, AI literacy, embodied metaphor, optics

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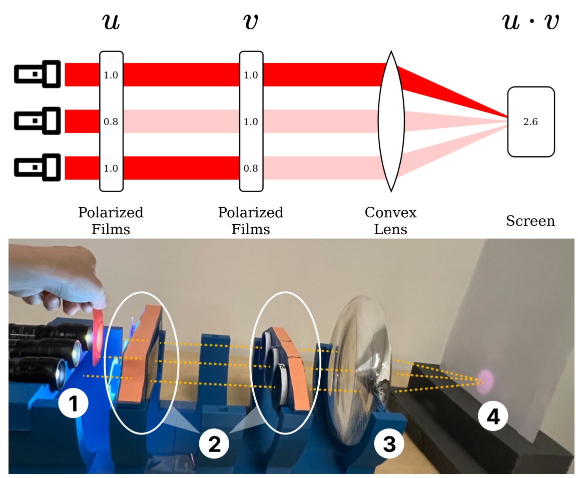

Figure 1: OptiDot: A tangible interface using (1) light beams, (2) two sets of polarized films, (3) a convex lens, and (4) the focused beam to manipulate the dot product.

1 INTRODUCTION

With the increasingly prevalent Artificial Intelligence (AI) applications in our daily lives, AI literacy has become essential for the young generation to make more informed and mindful decisions. Existing AI literacy education for children often treats AI as a black box and only introduces its high-level workflows and capabilities (e.g., image & voice recognition) (see [43] as a review) without explaining their inner workings. Such opacity may leave children at risk for inaccurate or oversimplified mental models of AI [30], which may become hard to change once formed [16]. More importantly, research shows that learning AI's inner workings empowers children to take action around the ethical aspects of AI technologies and relieve some stress of feeling "powerless" [42]. Furthermore, more technical AI literacy is needed for the young generation to meet the higher demand for AI-related computational capabilities at work by better collaborating with AI [10, 32, 50]. However, the underlying AI concepts, such as the dot product, are often overly abstract to young students due to their limited prior knowledge of math and computing [21].

Therefore, we propose new embodied learning experiences that utilize exploration with light beams. Embodied learning may benefit young students' conceptual understanding and memory retention by mapping abstract AI concepts with embodied metaphors, which use repeated sensorimotor patterns to represent knowledge [3, 18]. Two factors inspire the choice of creating optical-based embodied

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metaphors. First, the recent advancement of optical computing (e.g., optical neural network [13, 15]) makes the interaction with optical phenomena promising bodily experiences to reveal the inner workings of AI applications. Second, existing K-12 STEM curricula [8] also familiarize young students with many optical phenomena, such as light passing through and refraction of light.

We created a novel optical interface named OptiDot (Fig. 1) by utilizing image schemas - mental structures formed from recurring sensorimotor experiences [20]. Through five key image schemas (PART-WHOLE, BRIGHT-DARK, BLOCKAGE, MERGING, HUE), OptiDot connects AI applications (AI recommendation systems [34]) and abstract inner workings (i.e., data vector, the dot product) with concrete observation and manipulation of light beams. The AI recommendation system is chosen because it's one of the most popular and accessible AI technologies for the young generation and has a significant impact on what information they receive which hugely influences their opinions and behaviors [2, 26, 31]. The dot product is an algebraic operation that takes two equal-length data vectors and returns a value representing the similarity between the data vectors. It was chosen because it's one of the fundamental building blocks for numerous AI applications, such as feature engineering and neural networks.

With OptiDot, we investigated the research question: to what extent can OptiDot bridge the abstract concept of AI recommendation systems and the underlying dot product procedure with familiar sensorimotor experiences with light beams? Preliminary findings from 10 middle school students indicate the effectiveness of key embodied metaphors in OptiDot. We also discuss the design implications and limitations of optical-inspired learning technologies in AI education for children.

2 RELATED WORK

2.1 Teach AI to Children

Recent research in teaching AI knowledge to children has created various forms of interfaces and curricula to introduce students to the fundamental concepts and applications of AI. Most of them are web-based learning platforms, such as SmileyCluster [46], PRIMARYAI [12], AlpacaML [51], and Zhorai [28], LearningML [11]. AI knowledge is introduced through the lens of scientific inquiry learning [46], art [45], social studies [22, 48], and integration with other STEM domains [27, 49]. The most common approaches to make abstract AI literacy accessible for young learners include accessible data visualization [28, 46], embodied learning with gestures and body movements for model training data collection [16, 51], and gamification [17, 33]. With emerging research in AI education for children, more findings have been revealed showing that learning the inner workings of AI empowers children to take action against the ethical concerns of AI technologies [10, 14, 24, 42, 44], and support them to develop a more positive attitude. Research gaps, however, exist in understanding how to design specific connections between image schemas and abstract AI concepts [9].

2.2 Embodied Learning and Image Schema

Embodied Learning enables students to physically interact with the learning content and transfer their intelligence into the physical world [35], which can enhance their classification and recall [4, 4]. In addition, picking up, rotating, and dropping virtual pieces promotes 3D investigation and problem-solving [38]. Interaction with abstract concepts denotes the use of digital technology to materialize abstract concepts. Embodied learning suggests stimulating various motions for re-enacting 3D simulated phenomena [36, 37] which can improve children's comprehension of abstract action [39]. To design effective embodied learning, it is necessary to utilize image schemas as embodied metaphors to represent abstract knowledge. Image schemas are mental structures formed by repeated sensorimotor and subconscious experiences [18]. Common image schemas (e.g., PART-WHOLE, BRIGHT-DARK, BLOCKAGE, MERGING) can be categorized into groups of basic, space, containment, multiplicity, process, force, and attribute. For example, the PART-WHOLE schema is an embodied structure of a whole, parts, and configuration [25]. BLOCKAGE represents a scenario in which an object is stopped moving [5]. And MERGING demonstrates the stages of objects' relationship of coming together [7].

2.3 Optics for AI

Recent years have seen the development of AI, especially its application in digital transformation [47]. However, it requires large computer processing capability to implement AI, especially for deep artificial neural networks. Optical hardware-based AI has become popular recently due to its lower power consumption and faster speed, thus with the potential to solve the above-mentioned issue. This is also one of the reasons we chose optics in this paper. Another reason is that optics provides a sensorimotor experience to users. Also, one famous example of the application of optics in AI is the optical neural network [13, 15].

2.4 Light for Embodied Learning

Optical phenomena can be used to create embodied learning experiences. For example, the Light-Wall [23] has the intensity of light to represent the value of the stock in system thinking building blocks. Another system named EnergyBugs [41] used the time duration that the lamp can be illuminated to represent the amount of energy produced by the user's motion. It also introduced brightness differences to explain the energy consumption rate. Similarly, Lantern [1] used the intensity of the lamp to specify the time that has been spent for a group on one exercise during the recitation, thus improving the tutor-team interactions and the intra-team collaborations.

3 THE DESIGN OF OPTIDOT

3.1 Light as Creating Embodied Metaphors

Young learners are familiar with optical phenomena (Table 1 (2)), such as light beams and light brightness, through their daily life experience and the existing in-school STEM curriculum [8]. With image schemas related to the light (e.g., PART-WHOLE, BRIGHT-DARK, BLOCKAGE, HUE, MERGING) [18, 19, 29], we create OptiDot elements to represent concepts related to AI recommendation systems (Table 1 (1)). For example, the brighter the light is, the higher the value predicted by the recommendation system (Fig. 2.1). The dimmer the light is, the lower the predicted value is (Fig. 2.2).

3.1.1 Embodied metaphors for the data vector. A data vector typically consists of multiple attributes that describe the characteristics

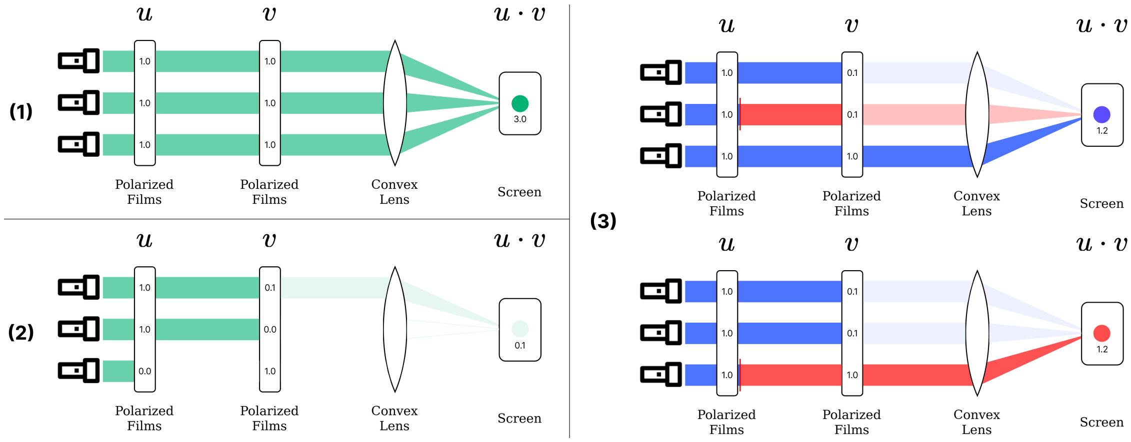

Figure 2: (1) & (2): Examples with different value settings; (3): an example of using a color filter.

of the data point. To make the concept of a data vector more concrete and accessible for children, we use an array of light beams as the embodied metaphor for an array of attributes. Individual light beams in the array represent individual data attributes in a vector (Fig. 3.1) (**PART-WHOLE**). The brightness of a light beam represents the value of an attribute in a data vector (**BRIGHT-DARK**). To change the brightness of a specific light beam, we utilize the polarized film, a material allowing only polarized light to pass through. By rotating a knob attached to a polarized film overlaid with another polarized film, learners can change the amount of light passing through the two polarized films stacked together. This embodies the change in a data value (Fig. 3.2) (**BLOCKAGE**). We calibrated the knob scale to make no light pass through the polarized films when the knob is rotated to the value of zero on the scale and make all the light pass through when the knob is rotated to the value of one on the scale.

An inspector is created with color filters for learners to differentiate different data attributes in a vector (Fig. 3.3). By placing a color filter in front of a light beam, the color of the light passing through will change to that color accordingly (see Fig. 2.3 for an example). This helps learners differentiate light beams that represent different data attributes in a vector or data vectors in the dot product (**HUE**).

For instance, a learner observes a more saturated blue light dot on the last projection screen after placing the blue color filter right in front of the left polarized film in a set of polarized films (Fig. 3.3), while the learner observes a less saturated blue dot on the last screen after placing the blue color filter in front of the second polarized film in the same set of polarized films. The learner can understand that the first attribute in the data vector has a higher impact/weight on the final output.

To investigate the different impacts/weights between two data vectors, a learner can (1) place a color filter right in front of the first set of polarized films, (2) observe the color projected on the last screen, (3) move the color filter in front of the second set of polarized films, and (4) observe the color change in the light dot focused on the last screen. If the color saturation in the light dot increases, the second data vector has a higher impact on the final output. If the color saturation in the light dot decreases, the first data vector has a higher impact.

3.1.2 Embodied metaphors for the dot product. There are two major operations in the dot product of two data vectors. First, multiply individual pairs of values of attributes in the same position of the two data vectors (e.g., the value of the first attribute in one data vector multiplies the value of the first attribute in the other data vector; the value of the second attribute in one data vector multiplies the value of the second attribute in the other data vector). Second, add up individual values from multiplications in the first step (Fig. 3.b & 3.c).

OptiDot unveils the two-step dot product through image schemas BLOCKAGE, MERGING, and BRIGHT-DARK (Table 1. First, the amount of light changes after passing through two sets of polarized films, which represent the multiplication of individual pairs of values in the two vectors (Fig. 3.a) (**BLOCKAGE**). For example, Fig. 2.2 shows multiplications of three pairs of values in two data vectors. Second, light beams converge after passing through a convex lens. This embodies the addition of all the products from the multiplications (Fig. 3.b) (**MERGING**). Fig. 2.1 is an example of the maximum amount of light that can merge from three light sources. In the end, the projection of the focused beam represents the output of the dot product and the brightness embodies the value (Fig. 3.c) (**BRIGHT-DARK**).

3.2 OptiDot Learning Activity Design

To evaluate the effectiveness of the embodied metaphors in OptiDot, we create three major learning activities that introduce the AI recommendation system and its inner workings (i.e., the concept of data vectors and the dot product). The first set of polarized films represents the user vector (i.e., values describing preferences toward certain product properties for users of a recommendation system). The second set is the item vector (i.e., values describing certain properties of products in a recommendation system). We chose snack recommendations as the content for three reasons: (1) snack recommendations may engage students in the activity with higher interest; (2) snack recommendations can provide a familiar and inclusive common ground to engage young learners with different

Table 1: Embodied metaphor schema to connect abstract AI concepts and methods with concrete bodily experiences.

	(1) AI Literacy	Image Schema	**(2)** Optical phenomenon for embodied learning
Vector	Concept: The array of attributes	PART-WHOLE	The array of light beams
	Concept: Attribute values	BRIGHT-DARK	The brightness of a light beam (the amount of light passing through)
	Method: Changing vector values	BLOCKAGE	Rotate a knob on a polarized film sheet to change the amount of light that can pass through the lens
	Method: Differentiating different attributes in a vector	HUE	Place a color filter in front of different torches
Dot Product	Concept: Multiplication	BLOCKAGE	One light beam going through two polarized films
	Concept: Addition	MERGING	The array of light beams going through a convex lens
	Method: Reading the dot product output value	BRIGHT-DARK	Observe the brightness of the focused beam

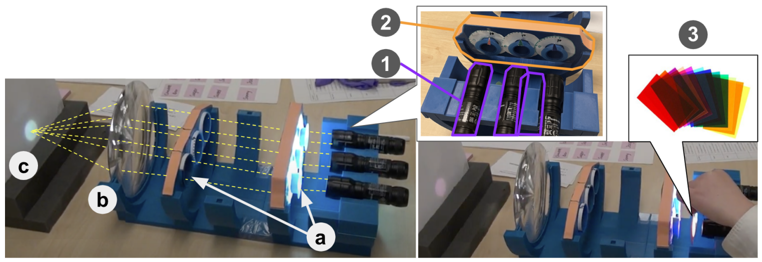

Figure 3: OptiDot embodied metaphors for the data vector: (1) PART-WHOLE (an array of light beams), (2) BRIGHT-DARK & BLOCKAGE (polarized films to adjust the amount of light passing through), (3) HUE (filters in different colors); embodied metaphors for the dot product: (a) BLOCKAGE (two sets of polarized films to adjust the amount of light passing through), (b) MERGING (a convex lens to add up all the light beams), (c) BRIGHT-DARK (the amount of light in the focused beam).

levels of exposure to AI technology; (3) the topic of snacks can be extended to the learning related to nutrition, which is also a crucial knowledge domain for children to develop [40]. We created three learning activities for students to interact with OptiDot, each lasting for about 10 minutes.

3.2.1 LA#1: Introducing an AI recommendation system to predict your snack preference. The first learning activity is structured to help learners understand OptiDot's snack preference predictions. It begins with learners adjusting the first set of polarized films to create a "user vector", reflecting their tastes in sweetness, salinity, and greasiness on a scale from 0 ("strongly dislike") to 10 ("strongly like"). Next, they adjust a second set of films to represent the sugar, salt, and oil content of a specific snack, like a chocolate bar. These vectors are used by OptiDot to predict the learner's preference for the snack, shown as a light dot's brightness on the final screen. Learners then compare this prediction with their actual snack preference and discuss OptiDot's prediction accuracy and rationale.

3.2.2 LA#2: Predicting different people's preferences for one snack. The purpose of the second learning activity is to help learners understand how OptiDot predicts different individuals' snack preferences. First, they set up a user vector for a person named Sammy, representing his preference for snacks' sweetness, salinity, and greasiness, along with an item vector for the cheesecake's nutritional properties. Learners then observe OptiDot's prediction about Sammy's liking for the cheesecake. Next, they change the user vector to represent another person, Jessie, and compare her predicted preference for the same cheesecake. This comparison of predictions for Sammy and Jessie facilitates a discussion among learners about the factors influencing OptiDot's diverse preference predictions for the same item across different users.

3.2.3 LA#3: Manipulating one value to alternate the prediction result. The objective is to provide an in-depth exploration of the mechanisms underlying an AI recommendation system. It starts with learners changing the item vector to represent potato chips, and they note that the system predicts Jessie will like them a lot. The main task for learners is to work together to make just one change in OptiDot that shifts this prediction from "strongly like" to "strongly dislike". They use color filters to identify different data vectors or attributes easily. The activity culminates in a discussion, where learners articulate their understanding of how their singular modification influenced the AI's final predictive output.

4 RESEARCH METHOD

4.1 Participants

Using study flyers and snowball sampling, we recruited five pairs of middle-school students for a preliminary evaluation study in the collaborative learning setting. There are six males and four females with ages ranging from 11 to 12 (Mean =11.5, SD = 0.53). The study was approved by the institutional Research Subjects Review Board.

4.2 Study Procedure

The study took place in an on-campus lab and lasted about one hour, facilitated by three researchers (Fig. 4). Students first completed a pre-survey collecting basic demographic information and assessing their prior knowledge of the dot product and AI recommendation systems. Then they participated in three OptiDot activities by following the instructions printed out. Researchers observed the entire session and provided facilitation when needed. After interacting with OptiDot, students completed a post-test. In the end, the researchers conducted a brief interview with the participants.

Figure 4: The preliminary evaluation of OptiDot with middle school students (N=10).

4.3 Data Collection

The research sites were set up by three researchers before the study. From the preliminary evaluation, we collected (1) video recordings from five cameras located at different places, (2) audio recordings of learners' discussions during the learning experience, and (3) pre- and post-tests on target AI literacy about AI recommendation systems and the inner workings (i.e., data representation, the dot product). Individual assessment questions are mapped with specific target knowledge components (Table 2 (1) & (2)). For the video recordings, the five different cameras cover the four different angles as well as the top view of the OptiDot system.

4.4 Data Analysis

We measured students' learning gains on different AI concepts related to AI recommendation systems (Table 2 (2)). A rubric is developed to score students' answers from the pre- and post-tests. Two researchers assigned scores to the answers independently, reaching a 0.87 agreement. Then researchers discussed and resolved the disagreements in the coding results.

Furthermore, we conducted a thematic analysis of post-interviews on students' subjective learning experiences. We derive an initial understanding of what design elements of OptiDot are effective and what design iterations are needed.

5 RESULTS

5.1 Learning Gains with OptiDot

The average differences of all questions between pre- and post-tests were normally distributed. A paired-sample t-test was conducted for the pre- to post-test (Table 2). The results showed significant increases for four questions assessing students' conceptual understanding of (1) the user representation, (2) the item representation, (3) the output in a recommendation system, and (4) the dot product procedure as the inner workings of a recommendation system, with p-values < 0.005. The learning gains significantly increase for the conceptual understanding of the multiplication in the dot product with a p-value < 0.05. However, the increase in the conceptual understanding of the addition calculation in the dot product is not statistically significant ($p = 0.739$). Furthermore, the mean pre-test results show that the participants in our preliminary evaluation study have little prior knowledge of the related knowledge components around AI recommendation systems and the inner workings of the dot product (Table 2).

The findings above indicate that the OptiDot activities are effective in supporting young learners with no or little AI and math prior knowledge to develop a conceptual understanding of how a recommendation system uses data vectors to represent a user and an item for the recommendation, the output of a recommendation system, and its inner workings of the dot product procedure and the multiplication calculation. The image schemas embodying these knowledge components are (1) **PART-WHOLE** for the array of data attributes), (2) **BRIGHT-DARK** for the attribute values in a data vector and for reading the recommendation output, (3) **BLOCKAGE** for changing the attribute values in a data vector and for the multiplication calculation in the dot product, (4) **HUE** for differentiating and investigating different attributes in a vector.

The non-significant increase in the knowledge of the addition in the dot product indicates the current OptiDot design for the corresponding image schema **MERGING**. In the current OptiDot, a convex lens is placed in front of the last project screen to merge all the light beams passing through the previous polarized films (i.e., output values from the multiplication step in the dot product). Learners read the output value from the addition on the last screen.

5.2 Design Iterations Needed

From the analysis of students' feedback provided during the interviews, we identified a few design iterations needed from the observation of learners' interaction experience and their feedback.

5.2.1 *Enhancing the light paths.*

Learners reported that it's challenging for them to view the value changes within individual steps in the dot product process while they are adjusting different polarized films. This is because, in the current prototype of OptiDot, the transmission of light beams between lenses is not visible with air as the transmission medium. Therefore, the changes in the brightness of the light beams are hard to show before the focused beam is projected on the last screen. In the future iteration, we can try out other transparent transmission mediums to experiment with how the light paths within the dot product process can be enhanced.

5.2.2 *Improving the knob design.*

We created six knobs that can be rotated to adjust the scale values in two vectors. In the current design, the knobs for the second vector are hard to rotate because of the limited physical space in the middle part of the OptiDot prototype. Furthermore, the current interaction design for the knob rotation often leads to learners blocking the light paths with their hands, which could cause confusion during the learning experience.

5.2.3 *Hard to read the output on the last projection screen.*

We found that learners find it hard to accurately interpret the final output value in OptiDot. With the nuanced change in the brightness of the focused light beam projected on the last screen, students felt less confident about whether they should interpret the brightness as high-level (i.e., a high value in the prediction result) or medium-level (i.e., a medium value in the prediction result). Such inaccuracy in the interpretation of brightness might be more severe in the learning scenario for multi-class prediction. This difficulty in reading the light dot more confidently and accurately might be a potential reason for the less effectiveness of embodying the addition operation in the dot product by merging light beams with a convex lens.

Table 2: Paired t-test results for pre-and post-tests (N=10)

(1) Assessment Question (Scores range 0-3)	**(2)** Knowledge Component	Pre-Test		Post-Test		*t-test*	*p*
		M	SD	M	SD		
How to describe a user for a recommendation system?	The user representation in a recommendation system	0.1	0.32	2.3	0.82	-7.89	<0.001
How to describe an item for a recommendation system?	The item representation in a recommendation system	0.1	0.32	2.1	0.88	-6.8	<0.001
What does a recommendation system predict?	The output of a recommendation system	0.4	0.516	2.8	0.42	-11.38	<0.001
How does a recommendation system calculate the prediction result with a user vector and an item vector?	The dot product procedure as the inner workings of a recommendation system	0.4	0.97	2.2	1.316	-3.48	0.0026
To calculate a user's preference (user vector = (1, 9, 2)) for a book (book vector = (7, 0, 1)), which of the multiplication below will happen?	The dot product calculation for a recommendation system (multiplication)	0.3	0.95	1.8	1.56	-2.61	0.0177
What's the numeric prediction result of a user's preference (user vector = (1, 9, 2)) for a book (book vector = (7, 0, 1))?	The dot product calculation for a recommendation system (addition)	0.6	1.265	1.8	1.55	-1.897	0.739

6 CONCLUSIONS AND FUTURE WORK

This work proposed OptiDot, an optical tangible interface, for children to learn about the dot product and AI recommendation systems. A preliminary evaluation indicated OptiDot's learning effectiveness and derived the design implications for developing interfaces utilizing optic-related image schemas as embodied metaphors

Physical constraints in tangible interfaces for embodied learning. With the optical tangible interface, many physical restrictions are introduced by the optical principles. For example, the distances between lenses are determined by the corresponding focal lengths. This leads to the fixed size of the interface and limits many different interaction design options. Second, to provide a clear view of both the light beams from the flashlights and the interface annotations, a very specific lighting condition in the physical environment is required. Potential enhancements could be augmenting the existing tangible interface with Augmented Reality (AR) to (1) support more gesture-based interaction with the learning content, (2) enhance the light path, and (3) support the interpretation of the output light dot for multi-class prediction scenarios. With improvement in this aspect, observing the light beams in OptiDot can be more convenient and effective. This might lead to a better learning outcome of the addition calculation in the dot product. Last but not least, the current prototype of OptiDot is not portable with the requirements of all different lenses and polarized films.

Activity design for learning AI ethics. In addition to the snack recommendation, more recommendation contexts (e.g., game recommendations, book recommendations, music recommendations) can be introduced to engage more young students with a diverse range of cultural backgrounds and personal interests. To further develop children's understanding of AI ethics, one of the most important AI literacy categories [6], OptiDot activities can be specifically designed to scaffold the discussion around the ethical issues around AI recommendation systems, such as the filter bubble, data privacy, and data fairness. For instance, the light source can embody users' personal data and raise children's awareness of potential privacy concerns.

Further data analysis and collection. First, we are planning to further analyze students' more detailed learning behaviors during their learning processes. To measure the learning processes, we are looking into students' verbal and non-verbal behaviors during their interaction with OptiDot. We pay special attention to those unexpected behaviors they have while interacting with OptiDot or interacting with each other. Second, we can investigate the unique learning benefits and limitations of learning through embodied metaphors by comparing students' learning behaviors and outcomes with (1) the tangible OptiDot, (2) a 2D-version OptiDot, and (3) video or text-based instructional materials. Furthermore, beyond the existing set of image schemas designed as embodied metaphors for learning with OptiDot, we can more systematically explore the mapping between other image schemas and essential AI concepts.

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