A Design Framework for Citizen-Science AI Platforms for Families

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More families are willing to spend time on citizen science projects, intending to cultivate awareness of sustainability efforts by participating in scientific research. As machine learning techniques are becoming more integrated into citizen science projects, it is becoming increasingly essential for families to understand how AI technology works. Based on our previous online workshops with 14 families on Coraland, a platform explaining image classification in the context of citizen science, we present four design principles that support the design of citizen science AI applications for families: (1) Provide scaffolds of activities, (2) Expose underlying logic of AI systems, (3) Support users envision new use cases, (4) Support ongoing evaluation and reflection. Following these design principles, we develop a new iteration of Coraland's platform design to inform the design of future citizen science AI applications. We conclude with the potential applications and limitations of the proposed design framework.

Additional Key Words and Phrases: AI Literacy, Family Interaction, Citizen Science, Explainable AI

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1 INTRODUCTION

Citizen science allows the public to participate in and contribute to scientific studies. Though many citizen science projects target families as participants, few studies were designed specifically for facilitating child-parent interaction. While prior research suggests that parent involvement in citizen science projects promotes studies' outcomes [9], Lewenstein suggests that a lack of proper child-parent interaction limits the goal of parental involvement in citizen science [12]. Besides families' involvement in citizen science, citizen scientists have started to employ AI systems on a large scale to make predictions on future trends in "the environmental domain" [13]. This paper defines AI systems as all platforms, tools, or applications that automatically generate outputs via pre-trained algorithms. The prevailing integration of such AI systems into citizen science projects raises the bar to participate in citizen science. While more families are involved in AI-supported citizen science projects, many of them participate without understanding the mechanics of AI systems due to the complexity of explaining concepts in AI systems. However, the lack of understanding of AI system leads to declined motivation, less thoughtfully collected data, and a superficial knowledge of the research content. Therefore, besides the child-parent interaction, properly explaining the underlying logic of AI systems is also urgently necessary to promote better outcomes.

To address the needs stated above, we ask the following two questions:

- **RQ1**: What design principles help families participate in AI citizen science projects?
- **RQ2**: How can we apply these design principles to existing citizen science projects?

Based on our observations from online workshops with 14 families on Coraland, we propose four design principles to facilitate the development of future AI-supported citizen science applications. Each principle proposes new potential features for existing AI platform for citizen science, Coraland. We then apply these proposed principles to Coraland and generate a new iteration of its platform design.

The main contributions of this work are

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Design Principles	Citizen-Science Platform AI Features
Provide scaffolds of activities	*"Hints": give users instructions through different stages of the activity.*
Expose underlying logic of AI systems	*"Compare with AI": allow users to compare activity results with AI results, and demonstrates system's underlying logic for any given activity*
Support users to envision use cases	*"Envision and share": ask to envision the AI applications via drawing, text, or audio. Enable sharing of these ideas.*
Support evaluation and reflection	*"Evaluate and contribute": 1. Ask participants to trick the AI system by finding outlier examples of data. 2. Pairs up participants to evaluate the difference between their choice of data sets.*

Table 1. Design principles for Citizen-Science AI Platforms

- Four design principles for future AI citizen science platforms focusing on facilitating child-parent interaction and exposing underlying AI logic.
- Demonstrating Coraland as an example of an application addressing the four proposed design principles (See Table 1).

2 RELATED WORK

2.1 Citizen Science for Families

"A citizen scientist is a volunteer who collects and/or processes data as part of a scientific enquiry." [16]. Citizen science programs allows the public, from children to adults, to participate in and contribute to scientific research. In addition, these programs have the unique ability to promote environmental sustainability. For instance, Christmas Bird Count (CBC) has replaced the tradition of Christmas "side hunts" and helped more people recognize the importance of protecting birds [1]. A growing number of families are deciding to spend weekends on citizen science projects, connecting with nature[11]. However, there are still limitations in existing citizen science programs when it comes to supporting families. Karen et al. suggest, "some guidance is needed, from a teacher, parent or other leader ... because 'citizen science, by definition, relies on co-operation between a range of experts and non-experts'[10]" [13]. In addition, Evans et al. claim that "family groups" are more engaged than others during a neighborhood nest watch [9]. Despite these findings, a design framework for citizen science targeting family interactions and parent involvement is lacking. Even in a program that was designed to involve parents, the guidelines for parents to support children remained undefined. An NSF project called "Parents Involved/Pigeons Everywhere" (PIPE) tried to "increase parents' involvement in their children's science education" by including them in the pigeon watch project [12]. Lewenstein et al. pointed out that "the goal of parental involvement was not necessarily achieved" because of "the frequent lack of child-parent interaction" [12]. As an evaluator, Lewenstein observed that despite the parents' willingness to participate, they "would sit or stand to the side, talking among themselves" while "children ... [were] actively looking at pigeon flocks, counting the numbers of pigeons of different colors, recording the data on the appropriate sheets" [12]. Design considerations for parent involvement are thus highly in demand in such citizen science programs.

2.2 AI-supported Citizen Science

The integration of AI systems in citizen science applications supports participants in completing the tasks without human assistance. For instance, iNaturalist[4] utilizes AI's predictions to help participants label unknown species. The eBird team also claims that "machine-learning algorithms can improve the predictive performance of eBird by guiding the sampling process" [2]. In addition to benefiting participants, AI systems also benefit scientists who propose citizen science programs. Compared to traditional citizen science projects that solely involve human efforts, AI-supported ones reach conclusions much faster and provide findings that may not be apparent to humans, by training machine learning models on the collected data. For instance, the eBird team utilizes machine learning models to "generate sophisticated Spatio-Temporal Exploratory Model (STEM) maps of bird migrations" [7]. In such cases, participants, including children and parents, are contributing to the machine learning training data sets through gamified activities.

As the integration of AI systems in citizen science projects prevails, explaining how machines will utilize user data becomes increasingly crucial. There is an urgent need to expose families to the underlying logic of AI and equip them with the knowledge required to provide valid input to AI-supported citizen science projects. Even though some explainable AI (XAI) systems educate people about machine thinking, few of them are designed in the context of citizen science. Introducing XAI systems into citizen science not only helps illustrate data usage but also helps families envision the real-world use cases of AI techniques. In the context of citizen science, families are better motivated to evaluate the AI's predictions, reflect on previous data input to AI applications, and even correct AI biases. Learning from XAI systems, families are equipped with a stronger ability to supervise and comment on scientists' research outcomes.

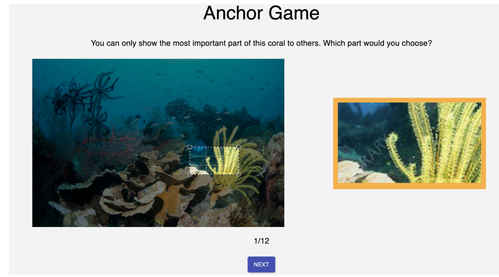
3 DESIGN PROPOSAL

3.1 Procedure

To facilitate the future design of AI-supported citizen science programs for families, we developed Coraland, a gamified platform that promotes families' understanding of machine learning by guiding them through a set of citizen science tasks. Coraland consists of two components, the Classification game and the Anchor game, present in the current iteration of the platform as "Coral Classifier" and "Coral Detector." The Coral Classifier presents 12 images of corals with various sizes, colors, types, and health conditions to participants. Participants can group the images into two categories and name the categories (see Fig. 1a). This open-ended game therefore allows participants to group images via any classification strategy. The other game, Coral Detector asks participants to summarize individual images of corals by selecting the most salient part of the images (see Fig. 1b). Similar to the Coral Classifier, the Coral Detector presents 12 images of corals to participants and shares the same image sets as the classification game. Through the two games, Coraland facilitates the participants to understand how machines process the images of corals collected by the public and eventually how machines can utilize the learned models to make predictions for a sustainable planet.

We recruited 14 families to participate in a 1:1 online workshop playing the web-based games on Coraland. To begin, families were asked the simple question "What is coral?" before they started playing. Then, children and parents decided their own roles in the collaboration, and played through the games. Finally, after each game, families reflected on the games via three questions: *1. How would computers do the same task? 2. Who can do this task better, you or computers? 3.How can we use this knowledge to do something good for the planet or do something useful?* Analyzing the results from the games, the feedback from the families, and our observed interactions, we concluded four design principles applicable to future AI-supported citizen science projects targeted at families. A new iteration of Coraland platform design was then generated based on the four design principles.

(a) Initial Coral Classifier interface for Coraland showing images of corals classified as healthy or unhealthy



(b) Initial Coral Detector interface for Coraland showing a image of coral being selected the most salient part

Fig. 1. The two gamified citizen science activities of Coraland

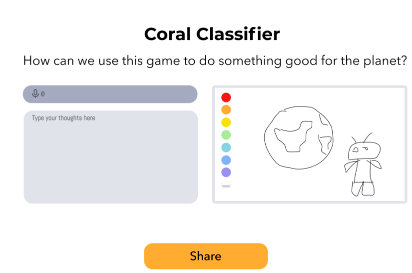
3.2 Design Principles & Strategies

3.2.1 Design Principle 1: Provide scaffolds of activities. From previous workshops, we observed that adequate scaffolding from parents provided children a chance to reflect and absorb what they learned, eventually promoted children's understanding of the AI systems. However, we observed that many parents failed to deliver effective interventions due to over-leading or low involvement. Furthermore, parents themselves sometimes got confused during the activities, and were unsure how they should interact with and guide their children. During one run of the Classification game, M.(a 7-year-old girl)'s father asked the researchers

> "What are we trying to do? What are we trying to do by doing this activity?" – M.(a 7-year-old girl)'s father

To reduce confusion and propose more precise guidelines for parents' interventions, we designed the "hints" feature for both the Coral Classifier and the Coral Detector which provided reminders for parents on how to play their roles as facilitators in collaborations. Fig. 2a shows an example of how the hints are worded to facilitate the collaboration between parents and children. We believe that giving instructions for parents at multiple stages through an activity helps avoid the situations of over-leading and indifference.

(a) Hints for parents



(b) Children envision use cases of AI

Fig. 2. New features of the Coral Classifier: hints for parents, prompts about real-world applications, and diverse image sets

3.2.2 Design Principle 2: Expose underlying logic. For families who participate in AI-supported citizen science projects, the prerequisite for valid model input is a clear vision of the underlying logic of AI systems. In our initial design of Coraland, participants understood this underlying logic implicitly by building connections between human strategies and machine strategies for the classification and detection tasks. R., an 11-year-old boy, claimed that AI systems worked differently from human brains. He compared his own thought process for classification to that of an AI system,

> "I have seen many pictures of coral and books and stuff like I would envision those and I would compare them, but the computer would not have that same ability to do that, it would just, like, be like, Oh, is it this? no, then it has to be the other thing, that kind of between black and white." —R., an 11-year-old boy.

Without explicit illustration of the underlying logic of AI systems, R.'s understanding of machine's strategies for classification was flawed. He failed to identify that AI systems' strategies for classification shared many similarities with humans' strategies, including learning correct classified samples first and comparing a new target image with the previously learned ones. It was not until his mother reminded him that the computer is powerful enough to remember lots of corals examples that he changed his mind:

> "It could figure out which family the specific corals are by comparing them to each other." —R., an 11-year-old boy.

Note that the reminder from R.'s mother was the key to the shift of R.'s opinion. It was his mother introduction to a machine's ability to remember samples which inspired R. to more accurately describe machine classification strategies more accurately.

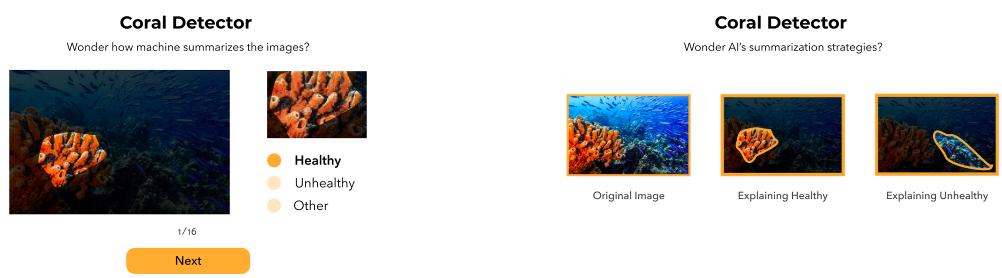
We observed that explicit illustrations from the parents significantly helped children understand the underlying logic of AI systems. However, it is challenging for parents to present these clear illustrations if they lack a computational background. To help parents, we designed new features for Coraland to visualize and demonstrate AI systems' logic. We also changed the activity names from "Classification Game" and "Anchor Game" into "Coral Classifier" and "Coral Detector" to indicate the connection between the activities and potential AI applications. By explicitly explaining the underlying logic of AI systems, families can better draw analogies or dissimilarities between human learning and machine learning.

For Coraland we built out features to support the explanation of two types of machine learning logic: classifying and detecting. In the "Coral Classifier" game, the "Compare with AI" feature shows an animation of how the AI system assigns a set of images into two groups with given prompts. Additionally, the "Show AI thinking process" feature shows participants how the AI compares a given image to an extensive network of images representing the ground truth of each prompt and then determines the image's designated group [5] (see Fig. 3b). This visualization provided insight into the connection and differences between human brains and machine brains in vision-related tasks. Similar to the same feature in the classification game, in the "Coral Detector" game the "Compare with AI" feature shows an animation of how AI processes an image, starting from identifying each identical object in the image to giving each object an evaluation score and finally determining and assigning images into groups [14] (see Fig. 4b).

3.2.3 Design Principle 3: Support users to envision use cases. Envisioning the use cases of AI-supported scientific research helps participants bridge the gap between their research contributions and the real-world application. Our online workshops on the initial design iteration of Coraland platform did not explicitly introduce the real-world applications of classification and detection tasks until post-activity questions. The discussion around the prompt *How can we use this knowledge to do something good for the planet or do something that is useful?* provoked families' thoughts significantly on the use cases of both the Coral Classifier and the Coral Detector. Provided with images of corals, we noticed families tended to situate the machine learning tasks within the context of marine sustainability.

(a) Animation of the AI’s classifying process (b) Visualization of AI’s classifying logic on a given image set

Fig. 3. Flow of the "Compare with AI" feature for the Coral Classifier



(a) Animation of the AI’s detecting process (b) Visualization of the AI’s detecting logic

Fig. 4. Flow of the "Compare with AI" feature for the Coral Detector

> “Applying an AI on corals to target where the corals are and how to save them, protect them.” —Ry. (a 7-year-old boy)’ s mother

> “Maybe scientists would put a tracker … on the submarine, and the computers controlling it. And they can take pictures again and then see if it’s big or small, and I can tell if they are corals or anemones.”—M., a 7-year-old girl

While participants were extremely generative in response to the discussion question, before the post-activity interviews, most families were confused about the direction and purpose of the activities.

> “I’m trying to understand what is the final product of the studies that you’re trying to get? I’m just trying to connect what you’re doing to what the final result is going to be?” —R. (an 11-year-old boy)’s mother.

Considering the significant improvements in participants’ understanding of real-world applications brought about by the post-activity questions, the new iteration of Coraland design embeds an activity based on this question right into the game itself. Given the prompt *How can we use this game to do something good for the planet?*, families are encouraged to express their ideas during the game via multiple formats, including typing, speaking, and painting (see Fig. 2b). In addition, we added a forum feature where children could share their ideas and also see other participants’ ideas. The new features build up a community where insights on sustainability are shared and sparked among participants. Furthermore, to expand the scope of participants’ vision in real-world use cases for AI systems, we augment our image data set with various types of images such as marine debris, terrestrial organisms, and terrestrial environments.

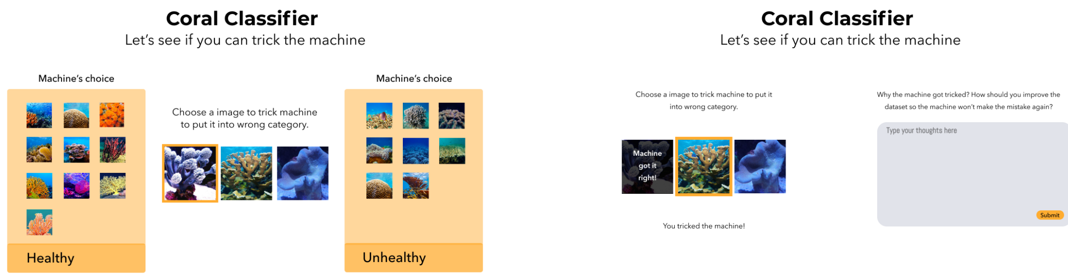
3.2.4 Design Principle 4: Support evaluation and reflection. Our previous design iteration of Coraland mainly focused on guiding participants to understand the processes used by machine learning algorithms to of classify and detect objects through a hands-on gamified experience. However, besides absorbing this information, families had few chances to contribute to the machine learning community. In most existing AI-supported citizen science projects [2–4, 6, 17], families are only invited to collect and annotate training data for machine learning models but are excluded from the model evaluation, project reflection, and error correction processes. We noticed that participants were not supported in optimizing the trained AI systems, even though many have already realized the existence of mistakes in such systems. E., a 9-year-old boy, claimed machines' errors were unavoidable and explained,

> "Because however it [referring to AI systems] was programmed, it might malfunction."—E., a 9-year-old boy.

A better platform design is needed to increase families' involvement in AI system optimization. Such a design would help families realize that AI systems are not always correct and encourage them to envision solutions to improve AI systems' outputs in different contexts, such as social justice and environmental sustainability. To address this shortcoming, we designed new features in the "Coral Classifier" that allow participants to select and provide example images for two given categories of the machine's choice. Three images are displayed in the middle of the interface. First, participants need to select an image that the machine would mistakenly categorize. If the machine successfully categorizes the image, participants will need to write down why they think the machine categorizes the image correctly. If the selected image tricks the machine, participants will need to write down how the machine could improve itself to prevent such mistakes (see Fig 5). Finally, participants are required to upload an image to help the machine improve its accuracy in categorizing coral images. Another approach to further facilitate the engagement of participants in the machine learning community is to add the feature of collaborations. This new feature in the "Coral Detector" game asked participants to pair up and complete the game with the same set of images. The computer will then display the image where their detector selections are most distinctive from each other. Participants need to write down or record their discussion about their choices of detectors and finally submit a detector agreed on by both participants. Such a feature not only motivates collaboration but also demonstrates how the machine learns to improves itself. Furthermore, the finalized selection of detector could be used to annotate data, thereby contributing to specific training data sets (see Fig 6).

3.3 Potential Application

Coraland's new design provides families with more opportunities to contribute to the AI-supported citizen science community. For crowdsourced projects that highly rely on trustworthy data input, training a large number of participants to collect data effectively and accurately within a reasonable time frame and cost is vital but challenging. For instance, Project Sidewalk, a project that allows participants to "virtually explore city streets to find and label accessibility issues", utilizes the manually labeled data to "train machine learning algorithms to automatically find accessibility issues" [15]. Reliable inputs significantly improve the accuracy of the AI system's predictions which eventually help more people with disabilities. The new design of Coraland offers constructive guidelines and instructions for a similar type of labeling activity, allowing families to participate and complete the data annotation process without researchers' assistance. Additionally, by exposing participants to the logic of AI systems and asking them to envision the real-world practice of AI systems, the new design significantly mitigates the issue that participants are not familiar with the purpose and outcomes of an AI-supported citizen science project. With more concrete knowledge of AI systems' logic and the research purpose, participants might provide more valuable and valid data towards AI systems. Additionally, the new design supports participants in



(a) Choose an image to trick the machine (b) Share insights and takeaways

Fig. 5. Flow of the feature that incites children's awareness of an AI system's limitations by trying to trick the machine

(a) Compare the Coral Detector results with partners (b) Ask partners to make one final selection together

Fig. 6. Facilitate collaborations among different participants of the Coral Detector game

identifying and correcting errors in the predictions made by AI systems. Upon locating an error, participants can analyze the reasons behind it, revise others' annotations and upload new samples to improve the model.

4 LIMITATIONS & FUTURE DIRECTIONS

Our study included children and families with different ethnic backgrounds and different languages, contributing to the diversity of our sample space. However, affected by the COVID-19 pandemic, only 14 families participated in our first iteration of Coraland workshops. In addition, all workshops were held in a remote 1:1 setting, which limited the level of communication between families and researchers and the interactions and collaborations across different families. Our research team is now focused on deploying our new design for future iterations, emphasizing the demonstration of AI systems' logic and enforcing interaction within and across families. In the workshops, 8 out of 11 families suggested expanding the variety of image sets when providing feedback. Furthermore, as prior research stated, when a task is interesting and appealing to students, they are likely to invest more effort and persistence in the given tasks [8]. We believe providing participants the options to select the topic of their interests would serve the purpose. Therefore, we intend to give participants options to select image sets of different topics as ways to invoke their persistence with tasks and raise their awareness of sustainability.

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