BEHAVIOUR & INFORMATION TECHNOLOGY
https://doi.org/10.1080/0144929X.2024.2313147

Taylor & Francis
Taylor & Francis Group

Shifting roles and slow research: children's roles in participatory co-design of critical machine learning activities and technologies

Tolulope Famaye, Golnaz Arastoopour Irgens and Ibrahim Adisa

Education and Human Development, Clemson University, Clemson, United States

ABSTRACT

Including children's voices in the design of learning activities and technologies has increasingly become a subject of conversation among researchers and learning designers. Research suggests children have lived experiences that position them as useful contributors in co-designing curricula activities or technologies they will use. However, one significant challenge in participatory co-design is engaging children in the co-design of curricula when they have not yet learned the disciplinary content within the curricula. We present our two-year participatory design-based research study in which we co-designed a Critical Machine Learning educational programme with different groups of children at two after-school centres over two consecutive years. In this paper, we characterize the roles children embodied in two cycles of participatory co-design and how the program's activities impacted these roles. Findings in this study suggest that in two participatory design-based research cycles, children embodied different roles of tester, informant, or designer of both AI learning activities and AI technologies. Based on this design-based research study, we propose that a 'slow research' approach that emphasises trust-building and a deep understanding of children's perspectives can be instrumental in achieving meaningful co-design outcomes.

ARTICLE HISTORY
Received 3 September 2023
Accepted 20 January 2024

KEYWORDS
Participatory design; children's roles; critical machine learning; co-design; AI education

1. Introduction

Historically, the responsibility for designing curricula has predominantly fallen on adults such as teachers, researchers, curriculum specialists, and education policymakers. These different adult groups possess the content knowledge and pedagogical expertise required to shape effective learning experiences. While the expertise and input of adults in curriculum design are crucial, there has been a growing recognition of the value of involving a key stakeholder – the child learner (Clauhs and Cremata 2020; Durl et al. 2022; Ottenbreit-Leftwich et al. 2023; Vartiainen, Tedre, and Valtonen 2020).

When children's voices are not included in the curriculum design, their interests and lived experiences may not be reflected in the content and activities (Bron and Veugelers 2014; Walker 2015). A curriculum designed without active input from its primary beneficiaries, the children, may miss opportunities to fully engage and motivate learners (Leat and Reid 2012; Vartiainen, Tedre, and Valtonen 2020). Such a curriculum may feel irrelevant and disconnected from their lives, resulting in disinterest and a lack of enthusiasm for learning. While researchers and adult designers may possess content knowledge and pedagogical expertise, they have a limited understanding of children's lived experiences, needs, interests, and ways of thinking (Guha, Druin, and Fails 2013).

On the other hand, children have a more profound understanding of their lived experiences, but they may lack the comprehensive content knowledge researchers and educators possess. Recognising this complementary relationship between adult experts and child learners, meaningful and effective educational programme design can potentially be achieved when children and adults work together collaboratively. Consequently, there has been a significant shift towards more student-centered and participatory approaches in design studies involving children and adults to create more relevant, engaging, and equitable learning experiences (Alves-Oliveira et al. 2021; Brooman, Darwent, and Pimor 2015; Druin 2002; Garzotto 2008; Stålberg 2018). For example, Brooman, Darwent, and Pimor 2015, found that involving students in the curriculum design process led to a more engaged and student-centered approach to teaching and learning. Clauhs and Cremata (2020) also found that including students' voices in the design of a music education curriculum increased participation rates among racialized student populations and impacted

CONTACT Tolulope Famaye tfamaye@g.clemson.edu Department of Education and Human Development, Learning Sciences, 209 Gantt Circle, United States

the demographic profile of the music class. In addition, studies (Carey 2013; Gillett-Swan, Winter, and Radovic 2023; Jones and Bubb 2021) suggest that children want to be heard and believe that they can offer value when given the opportunity to contribute to the design of their learning experiences. These studies reveal that children have the capacity to come up with new ideas and work collaboratively with others to create resources and experiences that are both meaningful and engaging.

When children are engaged in the design of technology and learning activities, research suggests that they can take on different roles throughout the process. Druin (2002) identified four roles that children can play: user, tester, informant, and design partner. Iversen, Smith, and Dindler (2017) added the role of the protagonist, giving the child more control over setting the goals of the project, making decisions about the design, and testing the final product. These studies suggest that the roles that children can play in the design of technology or learning activities give them varying degrees of agency during the design process that can provide an opportunity for children to have their voices heard and contribute their lived experiences to the design of technology or learning activities that are relevant to them.

Engaging children in the design of their learning environments is especially important for computer science-related curricula as it can help children develop a deeper understanding of abstract concepts and their practical applications (Dietz et al. 2021). By engaging in co-design activities with adults and peers, children can apply theoretical knowledge to solve practical challenges, reinforcing their understanding of how abstract computer science concepts can be translated into tangible solutions. In addition, engaging children in the design of their learning environments is especially important for computer science-related curricula as it can help promote equity and social justice in computer science classrooms (Coenraad et al. 2019). Historically, computer science-related fields have been perceived as exclusive and only giving access to dominant populations. Involving children in the design of computer science learning experiences can create a space where children's diverse perspectives, interests, and cultural backgrounds are integrated for a more inclusive curriculum.

Co-designing computer science-related curricula takes on added significance as the prevalence of artificial intelligence (AI) and machine learning technologies continues to grow. As these technologies become more widespread, the need to educate children about responsible consumption and the future design of these innovations becomes even more pronounced. AI and machine learning technologies can be incredibly beneficial, but they also can be harmful, particularly for minoritized populations (O'Neil 2017). As users of technologies and future designers, it is important for children to understand the potential for bias and discrimination in AI and machine learning technologies and to learn how to design these technologies that can be fairer and more equitable. In prior studies (Arastoopour Irgens et al. 2022a; Arastoopour Irgens et al. 2022b), we designed activities with and for elementary-school-aged children to (1) learn how to design and build machine learning applications for social good, (2) develop and express their thoughts around bias and discrimination in machine learning in ways that affect them and communities they care about, and (3) learning computational thinking practices. As prior work suggests (Vartiainen, Tedre, and Valtonen 2020), there is a need to introduce students to the ethical challenges surrounding AI applications and how to navigate them. While some studies (Ottenbreit-Leftwich et al. 2023) show that children are able to express existing knowledge around different ethical implications of AI, focusing on both positive and negative aspects of AI that could help or harm people, our findings go a step further suggesting that children were able to (1) pose and answer critical questions related to AI, such as: Who develops technologies? For whom are technologies developed? And what decisions are made based on the outputs of the algorithms? (2) Describe and discuss how dominant populations create the majority of technologies and that marginalised populations may be unjustly excluded or harmed when biased datasets are used to train machine learning applications, and (3) reimagine and build machine learning applications for social good to support marginalised populations, such as other children who are not being served by current technologies.

As our prior work suggests, engaging children in the co-design of their machine learning educational experiences facilitates the learning of computer science content and strengthens the connections between disciplinary content and children's interests and values. However, one significant challenge in participatory co-design is how to engage children in the co-design of curricula when they have not yet learned the disciplinary content within the curricula (Bonsignore et al. 2013). In other words, a paradox must be addressed that people cannot really be informed unless they participate, yet they cannot really participate unless they are informed (Eden 2002). One approach towards breaking this paradox is to recognise the different forms of expertise children possess and how their varied experiences serve as strengths during the co-design process. For example, in one participatory co-design study, Yip and colleagues (Yip et al. 2013) co-designed a science learning

application with children. Their findings suggest that children who have prior experience with designing technologies but limited domain knowledge, focused on the social features of designing technologies and provided more unconstrained ideas during the design process compared to children with less experience designing technologies. On the other hand, children in their study who had more domain knowledge experience were less likely to critique the technologies but provided more pragmatic and practical ideas regarding the design of the learning activities because they had some understanding of the science context. Thus, research has suggested that acknowledging and leveraging children's varied experiences can be a powerful tool for co-designing technologies with children. However, there is still a lack of systematic and reflexive methods regarding effective participatory co-design with children around designing learning environments themselves, not just technologies (Cumbo and Selwyn 2022). Moreover, research has not characterised the intersecting roles that children play in the co-design process as they are learning disciplinary content knowledge, building new technologies, *and* informing curricula.

Thus, this paper presents our two-year design-based research study in which we co-designed a Critical Machine Learning educational programme with two different groups of children at an after-school centre. Our goal was to characterise the roles that children embodied in two cycles of participatory co-design and how the activities of the programme impacted these roles. The research question in this study is: *What roles do children embody in participatory co-design cycles of an emerging machine learning educational program?*

2. Theory and background

This section provides an overview of the theories and research approaches that guide our research. We start by exploring theories which draw on the foundational theory of constructionism. We look at how constructionism and its related subsets are implemented in research, especially in practical studies with children which focus on learners' cultural backgrounds, societal contexts, and active participation. We emphasise the value of participatory, inclusive, and cooperative methods in these situations. We also highlight how these approaches are used to teach computing concepts to children, demonstrating the connection between theory and practice in education.

2.1. Critical situated constructionism

Our theoretical approach to learning is grounded in *constructionism* (Papert 1980), which emphasises the importance of externalising the learning of concepts through the creation of artifacts. By creating 'objects-to-think-with', learners actively (re)construct their understanding of a domain (Kafai and Resnick 1996; Papert and Harel 1991). In most cases, the object that is being constructed is computational in nature (Holbert and Wilensky 2019; Wilensky and Reisman 2006) and can be manipulated in multiple ways to represent conceptual ideas (Papert 1980). Additionally, when learners have access to multiple representations of concepts, they can make decisions about how to connect among these representations and pieces of their knowledge. The more connections learners make between objects, the richer their understanding of the underlying concepts related to that object, and ultimately, the higher the quality of the relationship with the object and concepts (Wilensky 1991).

Recent research has begun to explore *situated constructionism*, which incorporates the sociocultural aspects of the learning environment and the situativity of learning. This approach includes the role of the educators, the embedded histories and cultures within the learner-created artifacts, and the ways in which knowledge is distributed across people and technologies within a learning environment (Desportes et al. 2022). For example, Searle and Kafai (2015) developed learning opportunities for Native American children to create e-textiles, fabrics that embed electronic components, such as lights and microcontrollers, that reflect their cultures and values. Their studies investigate how indigenous youth engage in computer science and computational thinking practices by creating artifacts linked to their intersection of ethnic/gender identities and cultural histories, which extends traditional ideas around the individualistic nature of constructionism.

Recent work has also begun to explore ideas around *critical constructionism*, which focuses specifically on how learners lived experiences and values are related to issues within larger systemic structures. Critical constructionism principles encourage learners to question oppressive systemic structures that are personal and to reimagine more equitable futures by creating personally meaningful artifacts (Kafai, Proctor, and Lui 2019). For example, Holbert, Dando, and Correa (2020) invited adolescent Black girls to attend a series of Afrofuturism Design Workshops that would 'connect them with designers, artists, and educators to conceive, design, prototype, fabricate, and present their own "Wakandan Inspired" Afrofuturism artifact' (333). Through the creation of artistic objects, participants examined and critiqued their personal experiences as Black women, as well as the systems of oppression and destruction that affect their lives. Such critical constructionist

approaches decentre colonial ways of knowing and being to work towards more inclusive knowledge production that includes questioning and rebuilding oppressive systems through the construction of artifacts and technologies.

2.2. Participatory design-based research

Design-based research (DBR) is a series of approaches for producing new theories, artifacts, and practices that impact learning and teaching. In DBR studies, researchers systematically build and test new designs in natural learning settings and adjust various aspects of the designed context through cycles of experimentation (Brown 1992). The goals are typically two-fold: (1) to ground learning experimentation within existing theories, but at the same time, (2) to generate new theories of learning and teaching to explain phenomena and produce change in the world (Barab et al. 2004; Cobb et al. 2003). Although this work can be 'demanding in that it involves "building the plane while flying it"' (diSessa and Cobb 2004, 98), the benefits of DBR are that learning theories are developed in the appropriate contexts in which they will be used and through rigorous cycles of experimentation (Hoadley 2002).

Since its instantiation in the 1990s, DBR has been the foundation of countless studies that have improved educational theory and practice. However, traditional DBR has rarely addressed societal inequities regarding race, gender, class, and other forms of problematic power dynamics, which are inseparable from research and educational institutions in the United States (Bang and Vossoughi 2016; Vakil et al. 2016). Often, design decisions are treated as objective truth without consideration of the privileged positions of the researchers and the lack of involvement of all diverse stakeholders in the research, such as teachers, families, or children (Bang and Vossoughi 2016). In response, scholars have extended DBR into new areas regarding equity and participatory research lenses. *Participatory Design Research* (PDR) reimagines DBR as advancing learning theories in naturalistic settings through explicit attention to what forms of knowledge are generated, how, why, where, and by whom (Bang and Vossoughi 2016; Philip, Bang, and Jackson 2018). The goals are to generate new theories of learning with a focus on sustainable social change. These additions challenge existing power dynamics and roles among the 'researcher' and 'the researched' and reimagine partnering relationships in design research. Knowledge stemming from all stakeholders and participants is valued, and expertise is distributed during the design and research activities. For example, Arastoopour Irgens et al. (2022a) conducted a PDR study in an after-school community centre. They partnered with elementary-school-aged children to co-design learning activities in which children could critique inequities in existing technologies and then design and build machine learning applications for social good. Prioritising building relationships with children and staff, researchers spent several weeks volunteering at the centre without engaging in data collection or promoting their own research agendas. Rather, the researchers helped children with their homework and brought robots and games to play with the children.

The findings in the study described the co-design process of the learning activities, including the failures and tensions that emerged. In PDR studies such as this one, the co-construction of knowledge and artifacts may result in uncertain goals and tensions between collaborators, but through commitment and transparency, such tensions can be acknowledged and potentially worked through (Plummer et al. 2019). Moreover, such tensions in relational research become an integral piece of the scientific journey and, in turn, should be analyzed and publicised to further educational research (Arastoopour Irgens et al. 2022b).

2.3. Participatory design research with children in computing education

Research suggests that co-designing with children offers valuable benefits that empower children to have agency in their learning and foster a sense that they are heard and can influence and participate in their own education (Jones and Bubb 2021). For example, a participatory case study by Hussain (2010) conducted with children shows that through simple participatory techniques, children can give designers insight into their needs and desires. When co-designing a curriculum with children, their lived experiences and real-world contexts are considered, ensuring that the curriculum becomes more relevant, meaningful, and engaging for them. As Guha, Druin, and Fails (2013) aptly put it, 'Despite the fact that we were all 7-year olds once, no adult member of our team is a 7-year-old today … Today's children are experts at what it means to be a child today' (17).

In the field of computing education, research has explored children's involvement as co-designers of AI and machine learning technologies. Studies have explored how children's input and insights can influence the design, functionality, and user experience of AI-powered applications or interactive systems (Bonsignore et al. 2013; Druin 1997; Druin et al. 2003; Nissinen et al. 2012). These studies have emphasised the need

to give children more voice in the design of technologies meant for them. These studies have been essential for creating more inclusive and user-friendly AI technologies that cater to a wider range of audiences of children, including children with disabilities (Morrison et al. 2021) or those from marginalised groups (Buddemeyer et al. 2022; Hussain 2010). The results of these studies suggest that children have the capacity to be valuable contributors to the design process of interactive technologies, digital learning environments, and augmented reality experiences. Children are able to produce new ideas that are relevant to their own experiences and interests, and they are also able to provide feedback that can help to improve the usability and engagement of these technologies.

2.4. The roles of children in participatory design research

Aside from contributing broadly as co-designers of technologies, research has explored the specific roles that children take up when they engage in co-design. In the field of Computer Child Interaction, studies mostly focus on the roles that children embody when co-designing technologies for other children, each role representing different levels of engagement (Ahn et al. 2014; Hussain 2010; Kankaanranta et al. 2021; Pires et al. 2022; Speer et al. 2021; Theodoropoulos 2022). Evidence from various studies suggests that children can take up roles based on the depth of engagement or social interaction with peers or other adults during the co-design process, such as designers, evaluators, process designers, protagonists, and researchers (Clark 2010; Druin 2005; Frauenberger, Good, and Keay-Bright 2011; Jones and Bubb 2021; Theodoropoulos 2022). Druin (2002) characterised children as users, testers, informants, and co-designers. Children, as testers, interact with technology prototypes while adults observe their interactions and directly gather feedback about their experiences with the technology. Children as informants actively participate in dialogue during discussions, activities, and interviews that are specifically designed to gather design feedback and construct dialogue together. Finally, children as design partners allow children to elaborate on design ideas and explore usability improvements. Druin also articulated underlying dimensions in each of these roles related to the children's relationship with adults, relationship to the technology, and goals for inquiry.

More recent scholarship has expanded this continuum to include dimensions such as locations of participants, relationships to physical spaces, and scale of content or information available. For example, in one recent case study (Fails et al. 2022) involving the KidsTeam project in which children design technologies for other children, the roles of the child designers significantly changed when design teams primarily interacted in virtual spaces. One change was the shift in child–adult power dynamics. The researchers noted that children embodied the roles of co-designers more often and that they exhibited more autonomy in decisions around collaborations with their teammates, likely because they were situated in the familiar space of their own homes, rather than an external university lab setting.

These studies (Ahn et al. 2014; Hussain 2010; Theodoropoulos 2022) have shown that children can play various roles in the design process, from minimal interaction to complex, creative input. These roles include designers, evaluators, process designers, protagonists, and researchers. Druin's (2002) seminal work further classified these roles into users, testers, informants, and co-designers, based on the tasks, relationships, and goals of children in the design process demonstrating the diverse capacities and contributions of children, who are increasingly seen as active and creative partners rather than passive users of technologies. While research suggests that children can offer valuable insights, making technology more inclusive and user-friendly, engaging children in the co-design process, particularly in specialised fields like AI and machine learning, introduces various challenges and complexities. A primary concern is the limited expertise of children in these advanced technological areas (Druga et al. 2017). Their lack of in-depth knowledge of AI and machine learning can potentially limit the quality and applicability of their contributions to the design process. Guha, Druin, and Fails (2013) notes that while children may not be technology experts, they have their own unique perspectives, experiences, and interests that can inspire new and innovative ideas for the design process. Another challenge is the power imbalance and dependency between children and adults, especially in fields where children are not subject matter experts (Walsh and Foss 2015). Adults need to provide technical support and guidance, while also creating a participatory and empowering environment for children to share their ideas. Ethical concerns, such as ensuring the safety, privacy, and consent of child participants, are also paramount in any research involving minors (Clark 2010). Theodoropoulos (2022) notes that balancing the power dynamics between children and adults is essential in co-design activities, as adults must facilitate and value children's input while also making it viable and realistic. This balance is crucial for integrating children's perspectives in the design of sophisticated

technologies like AI and machine learning, where their input can make technology more inclusive and user-friendly.

Thus far, we have presented an educational framework that combines critical and situated constructionist learning theory with participatory design research. This framework highlights the agency of learners, especially children, as co-designers of technology and learning content, while also considering wider social and ethical challenges in education and technology design.

3. Methodology

3.1. Research design

In this participatory design-based research study, we explore how the roles of child participants evolved over time in the co-design of a Critical Machine Learning programme through two-year cycles of design and implementation. We present the experiences of the child participants as they engaged in the activities of the programme and provided feedback. We sought to understand how the roles child participants embodied changed over the two design cycles and how the activities they chose to provide feedback on impacted the roles they embodied. This section outlines the key components of our PDR methodology, including research context, participants, data collection, data analysis, and the iterative design process.

3.2. Context of the study

For this study, we partnered with two non-profit community centres (Center A and Center B) located in the southern part of the U.S. These community centres are focused on fostering community empowerment, promoting the well-being of individuals across all age groups, and encouraging community engagement through different social activities and amenities they provide. The community centres offer an after-school programme that runs from 2:15 to 6:00pm for children. To keep children engaged during this afterschool period, they provide different indoor and outdoor activities such as homework time, basketball, swimming, cooking, dance, and art. Centers A and B were equipped with a computer lab and a smart TV. The children had their chromebooks provided by their respective schools, which they used to complete school assignments or play games. The staff at centres A and B predominantly consisted of adults with over ten years working at the centre, with the staff-to-children ratio averaging 1:10. Furthermore, each centre is supported by a middle school counsellor who is available to offer additional assistance.

In spring 2020, we partnered with the first community centre (Center A) to co-design a programme for youth, and the participants for the study consisted of three researchers, six child participants, and two centre staff. This first iteration spanned approximately eight weeks from 01/24/20–03/16/20. This period included preliminary meetings with the directors of the centre to final interviews with child and adult participants. The following year, in the spring of 2021, we partnered with one more community centre (Center B) while maintaining our relationship with the previous centre (Center A). Our second iteration in spring 2021 took place in the two centres: Center A (where we had an existing relationship) and a new centre, Center B. For the second iteration, engagement with Center A lasted approximately five weeks, and engagement with Center B lasted approximately seven weeks from our preliminary meetings with the centre director and post-interview with child participants (see table). Our existing relationship with Center A made the engagement period two weeks shorter than Center B. This was because our research team had an established relationship with the Center A staff and children from the previous year, making us familiar faces to them.

3.3. Study participants

The research team consisted of an intergenerational co-design group of adult and child participants. Child participants were between ages 8 and 12 between 4th and 8th grade and were recruited through an open invitation issued by the youth centre. The youth centres had a fairly diverse member population in terms of socioeconomic status, gender, ethnicity, and child participants. Some of the children come from single-parent households, and some were on financial assistance. Some of the youth had prior experience with coding, but none of them had experience with machine learning or algorithms or had prior knowledge about social and ethical issues of machine learning. Adult participants consisted of researchers and youth centre staff. The youth centre staff comprised of administrative staff who have work experience with the youth centre for over ten years and had no experience with coding, machine learning, or algorithms. The researchers, led by the principal investigator, a university professor, and doctoral students, were members of a Lab at a university in the Southern part of the United States. See Table for demographic information on child participants (Table 1).

Since this was a PDR study, adults and children played various roles depending on the specific task

Table 1. Study participants overview.

Iteration	Center	Period of engagement	Child participants	Centre staff	Researchers
Cycle 1 Spring 2020	Center A	01/24/20–03/16/20	6	2	3
Cycle 2 Spring 2021	Center A	4/28/21–5/26/21	28	2	4
Cycle 2 Spring 2021	Center B	03/22/21–5/5/20	16	2	2

or activity that the group engaged in. As experts with content knowledge and pedagogical expertise, researchers sometimes led discussions with children; at other times, the researchers took on supportive roles, allowing children to lead, and in certain instances, they collaborated with children to design activities. The centre staff majorly took on supportive roles to help children during activities or researchers when a request was made.

At different points of the programme, children, researchers or staff took on different roles at different points of the programme. For example, when designing their machine learning technology, children worked on individual projects but had the flexibility of engaging with peers and researchers to elaborate on their designs. This open forum afforded children flexibility where they openly brainstormed ideas with each other or with any of the researchers. For instance, Lily walked up to a researcher and stated, '*I have an amazing idea! Probably some people will be able to do it if they try out my invention*'. She proceeded to explain her concept of developing and training a model that can recognise and distinguish between various gymnastic poses. In another example, Hannah worked with a researcher to develop her idea of a model that differentiates a banana from an apple:

Hannah:	I want to do something that can tell the difference between a banana and an apple
Researcher:	Great! (Speaks to the youth support staff) Can we get a banana and apple here? (Todd joins in the conversation.)
Todd:	You can search it [photos of bananas and apples] up on the internet.
Researcher:	That's true! Good thinking Todd

In this scenario, the researcher supported the child by helping them find fruits for testing their idea. Additionally, another child provided input to further develop the first child's idea by proposing that they search the internet for fruits in case the specific fruit needed was unavailable. The example shows some of the ways the researchers acted as design partners as they helped children develop their own machine-learning applications. In these examples, the researcher provided support to the children by listening to their ideas, asking questions, and providing feedback. This helped the children to identify problems that can be solved with machine learning, provided children with tools that they can use to build their applications, provided feedback on children's work and helped them to improve their applications and celebrated children's successes and encouraged them to continue learning about machine learning.

3.4. Programme design

In spring 2021, we began the study by engaging with the centre's stakeholders. For the first week, we visited Center A to observe the daily activities of the children and staff in their natural environment. During these 'getting to know you' sessions, we focused on establishing rapport with the staff and children, learning about their interests, and gaining insights into the culture within the space. During our observations, we noticed that the youth often formed small groups, engaging in activities such as playing video games on computers or phones, completing paper-and-pencil homework, or utilising their school-assigned Chromebook computers. We assisted the youth with their homework and any school-related tasks they had. We also offered our assistance to the staff in conducting their regular activities as needed. Through our interactions and observations, we discovered that some of the youth expressed boredom, while both the staff and youth were overwhelmed by the impact of the COVID-19 pandemic. Our initial visit and interaction with the staff and children at the centre enabled us to realise there was a need for pre-engagement activities that would pique the children's interest. This realisation prompted us to introduce a range of computational and robotic play and learning objects (Strawbees, Sphero robot balls, and Specdrums) for the children to explore and tinker with. While this was not initially planned, we decided to incorporate these activities after our first two days, observing that the children appeared to be idle or spent more time chatting and playing video games. The children freely interacted with the tools without being restricted to a specific structure of exploration. They could choose

what tool they wanted to explore and with whom they wanted to explore. Some children chose to work in groups, collaborating with each other, while others preferred to work independently.

This exploration soon became an icebreaker that provided us with a valuable opportunity to build a stronger rapport with the children and connect with them on a deeper level. This connection fostered a more positive and interactive environment for the children, staff, and ourselves, promoting a sense of trust, curiosity, and enthusiasm within the programme. Additionally, introducing these play activities to the children provided enriching opportunities for computational exploration, hands-on learning, and creative problem-solving and also served as a smooth transition into the activities of the programme.

We designed the activities by adopting specific activities from MIT's '*How to Train Your Robot and AI Ethics Education Curriculum*' (Williams and Breazeal 2020) that were simple enough for the age category of children in our study and addressed the critical part of Machine Learning that was relevant to our study. Table 2 shows the activities implemented with Center A in Spring 2020. Each activity session lasted approximately sixty minutes and before the next engagement with the centre, the researchers met to discuss observations and possible improvements to the previous activity and next activity.

The following year in the spring of 2021, we carried out a second iteration at two centres; Center A (the previous centre) and a new centre Center B. The activities of the programme were revised following the feedback from children and staff in the previous year of the spring 2020 session (Table 3). First, we added additional physical computing activities with Teachable Machine because children enjoyed tinkering with robots. Second, we provided more cohesive progression through the

Table 2. First iterative Program Design in Spring 2020 implemented with Center A.

Activity type	Description	Learning goals: *Children should be able to:*
Embodied Algorithm	This 20-minute activity encouraged group participation and critical thinking about algorithms in various contexts. Children are divided into small groups and given the choice of three activities. Discussion questions revolve around understanding what an algorithm is and recognising potential challenges in creating and sharing algorithms.	• Explain that an algorithm is like a recipe, providing step-by-step instructions. • Give examples of why it's important to use clear and specific instructions in algorithms. • Discuss the idea that different people might have different ways of doing things, and that's okay.
Input Output Algorithm	In this activity, children use construction paper, markers, and large post-its to create illustrations that represents input, algorithms as the set of instructions for creating an output. The purpose of this activity is to help children understand that algorithms are like recipes, with inputs, procedures, and outputs. The key questions are designed to help children think about the different parts of an algorithm and the purposes of these parts.	• Identify and describe the key components of an algorithm, including inputs (ingredients), procedures (instructions to change input), and outputs (results). • Use examples such as basketball shot, dancing or making a PB&J sandwich, to identify the different components of algorithms that can be found in these examples
Google Image Search	Children engaged in a hands-on exploration of Google Image Search, encouraging them to think critically about how algorithms work, the subjectivity of search results, and the impact of device-specific variations in search outcomes. It sets the stage for further discussions on algorithms in digital technologies.	• Identify and describe components of algorithms in a Google Image Search (inputs, procedures, and outputs.) • Express their opinions on whether the search results align with their expectations. • Explain any differences in search results
Teachable Machine Activity	In this activity children learned the importance of training and test data in AI and recognising the significance of quality training data and they got to their own machine learning models and tested them on their peers.	• Demonstrate that training data is used to teach algorithms how to perform specific tasks and adapt to desired behaviour. • Demonstrate the ability to create machine learning models using provided tools or materials. • Explain the process of testing their machine learning models on their peers or classmates.
Video Discussion	For this activity, children watched two videos about AI/machine learning and algorithmic bias afterwards discuss the potential for bias in AI/machine learning systems and the importance of taking steps to mitigate it.	• Identify instances of potential bias in AI and machine learning systems. • Explain how algorithmic bias can lead to unfair or inaccurate results in AI systems. • Recognise the real-world impact of biased AI on individuals and communities. • Discuss why it's important to take steps to mitigate bias in AI and machine learning. • Express empathy and concern for the potential harm caused by biased AI.
Redesign of an existing app	Children chose a technology (YouTube, Google, SnapChat, TikTok, Twitter, Facebook, Facial Recognition software) and redesign the technology to be more fair and equitable. The activity was designed to enable children to think critically about the ethical implications of technology design.	• Identify and explain ethical concerns or biases present in the chosen technology. • Propose specific design changes that aim to make the technology more fair and equitable.

Table 3. Second iterative Program Design in Spring 2021 implemented with Center A and Center B.

Activity type	Description	Learning goals *Children should be able to*
Pizza Algorithm	Children are asked to write an algorithm to make the 'best' pizza. This activity allows them to explore what it means to be the 'best' and see how their opinions are reflected in their algorithms.	• Define algorithms and provide examples • Write a recipe for making a pizza to enable understanding of the components of an algorithm • Reflect on how to optimise their pizza algorithm in order to make sure it is detailed.
Helpful and Harmful Technology	Children create a list of technology that they use in their daily lives and discuss with each other whether or not it is helpful or harmful technology and why.	• Share personal beliefs about technology, algorithms, and AI • Identify harmful and helpful examples of technology.
Google Search	Children search different topics using Google search engine and discuss representation and bias issues related to these searches.	• Define machine learning • Provide examples of machine learning algorithms in the real world. • Discuss ethical dilemmas surrounding technology and algorithms in the real world. • Share personal beliefs about technology, algorithms, and AI.
Google's 'Quick, Draw!'	By exploring Google's 'Quick, Draw!' children understand that is a form of AI that learns from the drawings that people create when they are playing with this tool.	• Provide examples of machine learning algorithms in the real world. • Discuss ethical dilemmas surrounding technology and algorithms in the real world. • Share personal beliefs about technology, algorithms, and AI
Cat and Dog Teachable Machine	Using Google's teachable machine children build a cat-dog classifier but are unknowingly given a biased dataset. When the classifier works better on cats than dogs, the children have the opportunity to retrain their classifiers with their own new datasets.	• Use data sets of pictures to train image classifiers. • Identify potential biases in training datasets. • Minimise potential biases by altering training datasets. • Explain how the composition of training data affects the outcome of a supervised machine learning system.
Build Your Own Teachable Machine	Children create their own machine that recognises images, poses, or sounds using Google's Teachable Machine. They train their machines using items or images that they choose and also test their peers' machines for functionality and bias.	• Find and use data sets of pictures to train image classifiers. • Identify potential biases in training datasets. • Minimise potential biases by altering training datasets.
Coded Bias	Children watch the 'coded bias' trailer video and engage in a discussion on how bias can exist in Machine Learning applications that are used in everyday life. Through this activity, children are encouraged to consider how they can make their robots helpful to everyone, regardless of their background or identity.	• Discuss ethical dilemmas surrounding technology and algorithms in the real world. • Discuss algorithmic bias issues and solutions that are of interest and of importance to them and their communities.
Robot story	Children use poster paper and markers to draw and write a story about a robot that can help people. Children are encouraged to create fantastical stories.	• Design a superhero robot for social good
Building a Superhero Robot	With adult facilitation, children use machine learning block-based programming to train a robot prototype built based on their story. Adult facilitators encourage children to train a classifier, programme a robot prototype to respond to the classification algorithm, investigate bias in their training data.	• Train simple machines and robots to classify images. • Find and use training data to train a classifier and mitigate bias in their training datasets • Programme a robot using a combination of classifiers and block-based programming. • Design and build robots that could solve real-world problems for social good.

activities to better prepare children for the next tasks. Third, we provided opportunities for children to tinker with existing machine learning applications through structured activities before allowing them to create their own machine learning applications in order to better prepare them for creating their own applications.

During our initial four visits to the centres, our primary focus was on building rapport with the stakeholders and making them feel at ease with us as researchers. We engaged in conversations with the children, assisted them with their homework, interacted with centre staff, and introduced computational and robotic tools for the children to explore. Each activity session (60-minutes) consisted of a review of the previous day's lesson, individual or group activity, and show and tell, which led to group discussions. In order to give children a measure of agency we allowed them to decide if they wanted to work in groups or pairs for each activity. The research team met weekly to review the discussions and activities that took place during the previous session and plan the following week's session. We jointly reviewed the transcript and videotape of each session to study the children's thinking. Thus, our process was emergent; our evolving view of the children's experiences was the basis for redesigning the subsequent activities. Engagement with each youth centre was for seven weeks and consisted of 21 sessions 2–3 times weekly interactions, each lasting approximately 2 h.

3.5. Data collection

We present data collected primarily through reflective interviews and triangulate with observational field notes and recorded videos. We repeatedly watched the

video recordings and selected data only those sections of the video that provided rich information and context about children and adult interactions during the programme. Reflective interviews were conducted with child participants to gain a deeper understanding of children's perspectives, motivations, and cognitive processes towards the programme (Roulston 2010). These interviews provided valuable qualitative data that helped the researchers to understand the programme from the perspectives of the participants. Non-digital artifacts, such as paper illustrations, were collected during the reflective interviews to document the child participants' creations and contributions during the programme. Digital artifacts such as machine learning models were originally created and collected during the activity sessions but were presented to children during the interview in order to understand/provide opportunities for students to provide more information on the motivation of their design choices. The triangulation of these data sources helped to provide a richer and more nuanced understanding of the child participants' experiences with the Critical Machine Learning Education programme. Video recordings were used to document the child participants' experiences and interactions amongst themselves and with adult participants during the programme. These recordings provided a visual representation of the child participants' work and helped the researchers to understand the role of the adult participants in supporting the child participants' engagement. The information collected from these data sources was used to inform the analysis of the interviews and to develop the findings of the case study. The researchers conducted interviews with six children in the spring of 2020 and twelve children in spring of 2021. Some of the interview questions focused on the future design of the programme such as *If we worked together on designing a new program for you and your friends, how would you help us with the design? Do you want to draw some of your ideas of the different activities or what the space would look like?* Other questions focused on enabling them to reflect and review the activities, such as; *How would you change the Google Teachable Machine activity to make it more fun or interesting? How would you change the App redesign activity to make it more fun or interesting? How would you change other activities?* The interviews lasted approximately 12–15 min with each child participant. All interviews were audio recorded and transcribed for analysis.

3.6. Data analysis

We utilise Quantitative Ethnography (Shaffer 2017), an emerging methodology to gain a comprehensive understanding of the phenomena under investigation. This approach combines quantitative statistical analysis techniques with ethnographic approaches, allowing us to uncover patterns, trends, and contextual insights within the data (Shaffer 2017). The statistical analyses allow for discovering unexpected patterns in datasets and measuring the strength of relationships among variables (Shaffer 2017).

The ethnographic analyses allow for interpreting meanings behind what the participants are doing, saying, and illustrating in order to tell their stories (O'Reilly 2012). From an ethnographic perspective, data that is collected from the children can be referred to as small-d discourse – ways of acting and interacting in the world that we observe from individuals (Gee 2014). Using Quantitative Ethnography, discourse can be computationally analyzed to understand broader patterns of interactions that can be attributed to group culture. These patterns of discourse are known as big-D Discourse and are ways of 'talking, listening, writing, reading, acting, interacting, believing, valuing and feeling (and using various objects, symbols, images, tools, and technologies)' that are unique to a particular group of people who share common ways of being and thinking in the world. In this study, we collected the child participants' discourse data (small-d) from reflective interview data and their non-digital artifacts. Non-digital artifacts presented in this study are illustrations made by the child participant during the interview session.

The initial step of the analysis involved the lead researcher and a second researcher independently immersing themselves in the data by reviewing field notes, interview videos, and interview artifacts (Charmaz 2004). Field notes and artifacts were transcribed and included in the data analysis and emerging themes were applied as children's interviews were analyzed to reconstruct and better understand the events and interactions that occurred during the design process. The researchers met to discuss initial broad patterns in the data related to children's roles in co-design and reached an agreement on open coding (Saldana 2021). After several joint review sessions of identifiable codes in the data, we identified two categories: (1) codes related to children's roles and (2) codes related to the context. Children's roles referred to if the child was providing feedback from a specific function perspective such as testing or designing an activity or technology. We identified three roles children embodied in the data (tester, informant, designer). The second category, *context* refers to the context in which the child was immersed in the role (*AI technologies* and *AI learning activities*). We refer to the context of *AI technologies* as activities

Table 4. Codebook: embodied roles and activity contexts.

Context	Child roles	Definition	Example
AI Technologies	Tester	Children **talking about using and testing AI digital technologies** (Scratch AI, programming AI robots, Teachable Machine models) by describing their experiences using AI digital technologies.	'I just liked testing it [teachable machine model] and I got other people to hold it [the object] from different angles and see if it [the model] worked'.
	Informant	Children **talking or sketching about improving AI digital technologies** (Scratch AI, programming AI robots, Teachable Machine models).	'And so, I realized that you needed to add different feelings to each color. So, for each color, I inserted a different texture . . . '
	Designer	Children **talking about, sketching about, or demonstrating designing and/or building AI digital technologies** (Scratch AI, programming AI robots, Teachable Machine models). Design includes **continuous ideation, reflection on work done to identify areas of needed improvements, brainstorming, and crafting prototypes** of AI digital technologies.	'I like took pictures of me doing backbends or the tree [yoga pose], and then I took multiple pictures of them [the yoga poses] I trained my machine to recognize those two things [backbend and tree pose]'.
AI Learning Activities	Tester	Children **talking about engaging in designed learning activities** (Google quick draw, coded bias video, playing robots, interest boards) by describing their experiences in various activities.	'I really liked the robots. And I also really liked when we got to do, like [pause], this kind of involves robots, but like when we had to come up with our hypothetical robots'.
	Informant	Children **talking or sketching about improving designed learning activities** (Google quick draw, coded bias video, playing robots, interest boards)	'The only thing I would probably change is if we had more time to talk about it, so we could go in-depth on the different algorithms in different apps'.
	Designer	Children **talking about, sketching about, or demonstrating designing or building learning activities** (Google quick draw, coded bias video, playing robots, interest boards). Design includes **continuous ideation, reflection on work done to identify areas of needed improvements, brainstorming, and crafting materials** for learning activities	'If you want to stay in that station, you can. But sometimes it gets overcrowded because some people have ones that they really want, so I feel like that's not good. They just walk over to any station they want'.

that enabled children to explore AI technologies to design their own AI technologies. These activities involved creating algorithms, training, and testing AI machines, and designing programmes to control robots and were conducted using robots and AI applications (Table 4). In the context of *AI learning activities*, we refer to both plugged and unplugged activities in which children do not directly engage in the creation of AI but instead utilise tools to interact playfully with pre-designed technologies or participate in meaningful discussions about AI and bias (Table 4).

As we delved further into the data, we discovered that children took on distinct roles depending on the situations they were in. For instance, a child might act as a tester when giving feedback on a learning activity and as a tester when designing their machine learning applications. This insight led us to recognise the importance of specifying the context alongside the identified roles to comprehensively describe our findings. In other words, by pairing the codes, we derived six final codes; *AI technologies tester, AI technologies informant, AI technologies designer, AI learning activities tester, AI learning activities informant, and AI learning activities designer*. Table 4 provides details of the roles and contexts.

After quantifying the coded data, we used the Epistemic Network Analysis (ENA) 2.0 webtool (Marquart et al. 2018) to measure and visualise the relationships among the roles the children embodied in each cycle of participatory design and the context in which they embodied these roles. ENA measures the connections between discourse elements, or codes, by quantifying the co-occurrence of those elements within a defined stanza (Shaffer 2017; 2018). Stanzas are collections of utterances that are topically related. Once the size of a stanza is identified, for any two codes, their strength of association is computed based on the frequency of their co-occurrence within each stanza in the discourse. In this study, we defined a stanza using a sliding window (Siebert-Evenstone et al. 2017) of four lines to capture the recent temporal context of the discourse. Thus, co-occurrences of codes were calculated if they occurred within four lines of a child's turn of talk in an interview or a discussion-based activity.

After defining the stanza, each child's co-occurrences within each design cycle were summed and each child's discourse was visualised as a weighted node-link network representation. This single network represented a summation of one child's co-occurrences within a cycle in the programme. In the weighted networks, thicker links in the weighted network represent codes that co-occur often, and thinner links represent codes that co-occur less often.

To analyze several networks at one time, we used an alternative ENA representation in which the centroid (centre of mass) of each network was calculated and plotted in a fixed two-dimensional space that was mathematically created by conducting a multi-dimensional

scaling routine and a sphere-normalization. The space is interpreted by examining the location of the nodes in the two-dimensional space and evaluating the goodness of fit. In this analysis, both the Spearman and Pearson goodness of fit measures were .97 and .98 for the x and y axis, indicating the location placement of the nodes was reliable. For more detailed mathematical explanations of ENA, see work by (Arastoopour Irgens and Eagan 2022c; Bowman et al. 2021; Shaffer, Collier, and Ruis 2016).

4. Results

Our results highlight children's various roles in the Critical Machine Learning programme across two cycles. First, we present two vignettes illustrating children's experiences and motivations as testers, informants, or designers of AI activities and technologies in each cycle. Then, we compared the outcomes of both cycles to clarify how these roles varied based on programme activity design decisions and modifications.

4.1. Cycle one -Spring 2020: children as testers, informants, and designers of AI learning activities

During the first programme cycle we found that children primarily acted as testers, informants, and designers of AI learning activities. They embodied these roles by (a) providing feedback about their experience with the programme activities, (b) drawing illustrations of imagined learning spaces, and (c) verbally sharing ideas with researchers during the reflective interviews.

4.1.1. Example: Talia's stations

During Talia's interview, a researcher asked her to make suggestions for the improvement of the programme. Talia described wanting flexible learning spaces with various stations that allowed children to explore AI technologies. The researcher provided Talia with paper and pen and asked Talia to draw her vision. Talia drew a learning space with five different stations situating a '*technology station*' at the centre of the learning environment (Figure 1).

Describing stations one and two she explained

> *So this station* [pointing to station one] *is the game table with regular games and then board games. Station two is basically a screen thing … You know what a green screen is?* [asking the researcher who responds in affirmative] *Yeah, something like that.*

Further prompts by the researcher indicated that children would create and edit videos at station two. Talia

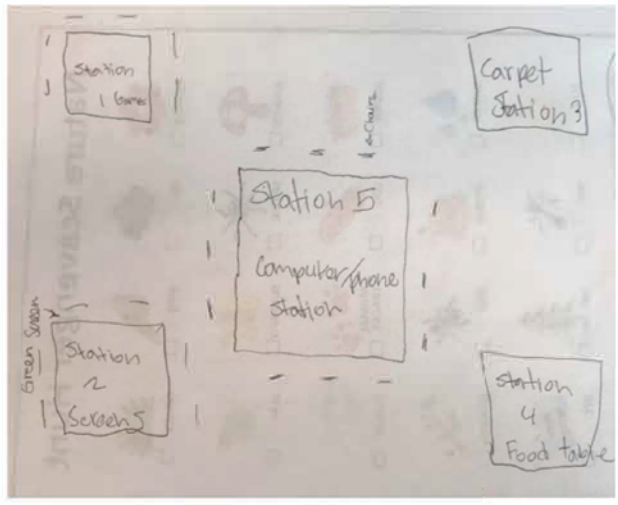

Figure 1. Talia's drawing of the learning space setup.

described station four as the '*the food table*' and station 3 as a space with '*a carpet area where you sit down, or basically a reading station with eBooks*' about '*different kinds of stuff. I like drama books and stuff*'. In this example, Talia provided suggestions for the design of the learning space in which AI learning activities could occur. Her suggestions as an **informant** and **designer** was to improve the programme by redesigning the physical learning environment to allow for flexibility and creativity by suggesting a space for games, green screen for video editing, an open space with a carpet for reading, and a food station.

At the centre of her diagram Talia drew station five, which was the largest station. When describing this station she stated, '*And then for station five, you got all the chairs around it and then you have a computer and phone station … So, in the middle, it'll be electronic*'. In her design, she assigned technology activities a central position by placing it at the centre of the learning space and drawing it as the largest station, suggesting that she recognised the central focus of interactive technology in the programme. She further described this station as having a large table with computers surrounded with chairs such that children could work at this central spot to code and create apps.

In this example, Talia's drawing establishes a connection between her role as an **informant** and **designer** of AI learning activities through her representation and placement of these stations. In her drawing, she assigns a central position to station five, a station that she envisages will allow children engage in technology activities related to the making of AI applications. This central placement suggests that Talia recognises the significance of hands-on AI making activities and the central placement allows for easy access to her 'technology station' by

children. Talia further adds to the design of the programme as she assigns stations (stations 1, 3, and 4) as additional learning stations. She envisaged that these stations would allow children explore additional activities that would supplement AI creation, such as playing robots, games, Google Quick Draw, and group discussions. Through her illustration and description, Talia embodied an informant as she makes improvements to the current activities while also designing a new activity space for AI and technology learning and creation.

When the researcher prompted Talia for suggestions for AI learning activities in the technology station, she suggested designing an app. Talia referenced how she was a **tester of the AI learning activity** in the programme using Google Teachable Machine. Then, she added, '*I like coding personally, and I think that would be good… Basically, to do stuff for apps and create them and fix them. I like that*'. When the researcher prompted her for the specific kind of app she would be interested in creating, she made reference to a personal challenge. She stated:

> I struggle in science. I would probably make a science app. I know a lot of people–my friends and close people that I know–who struggle very bad in science because it's hard. But I would create an easier app to help you understand a way of learning science.

In this excerpt, Talia suggested creating a science education mobile application to help children like herself who struggle with science in school. She mentioned a collective struggle with the school subject of science. Thus, she expressed a desire for developing technologies that would be 'easier' for her and her friends to 'understand a way of learning science'. Talia did not expand on what this 'way' of learning science could be, but her language suggested a potentially innovative approach for engaging in science knowledge and practices and her values around helping her peers improve their academic performances. This excerpt was the only time Talia discussed designing AI technologies themselves.

Referring to the Google Teachable Machine activity, Talia suggested opportunities for designing a variety of models. She explained

> Instead of smiling and frowning, you should do happy and attitude faces and stuff like that, and mad faces… instead of doing just faces, I feel like you should do what Noah did. When he did baby Yoda and stuff like that … You should do creatures and more creativity for it. That would be fun.

Here, Talia suggested that researchers provide more guidance for building a variety of Google Teachable Machine models beyond smiling faces and frowning faces. She suggested a more complicated model of introducing different emotions which she referred to as '*attitude faces*'. In addition, she suggested introducing models that recognise objects that exist within children's lived experience, making reference to a popular media figure, '*baby Yoda*'. Talia's suggestions revealed her interest in having more resources for creating diverse Google Teachable Machine models that allow children to incorporate their interests and creativity into creating machine learning applications.

In Talia's example, we can see a child embody and connect among the roles of tester, informant, and designer of AI learning activities. She used her sketched diagram to inform and design the curriculum by describing activities such as games, video creation/editing, and using Google Teachable Machine to design and build a science education mobile application. Visualising her discourse, Talia's network (Figure 2) shows strong connections among testing, informing, and designing AI learning activities, which supports the analysis above. These connections were evident in her suggestions for the design of the programme, as she proposed a variety of activities that would allow children to explore AI technologies in a variety of ways in a designed learning environment.

4.2. *Cycle two – Spring 2021:* children as testers, informants, and designers of AI technologies

In the second cycle, children were engaged in more activities than the first cycle. We made modifications to the five activities adopted in cycle one based on feedback from the children in cycle one and included four more activities for the second iteration. In this iteration, children engaged in Pizza Algorithm, Helpful and Harmful Technology, Google Search, Google's 'Quick, Draw!', Cat and Dog Teachable Machine, Build Your Own Teachable Machine, Coded Bias, Robot story, Building a Superhero Robot.

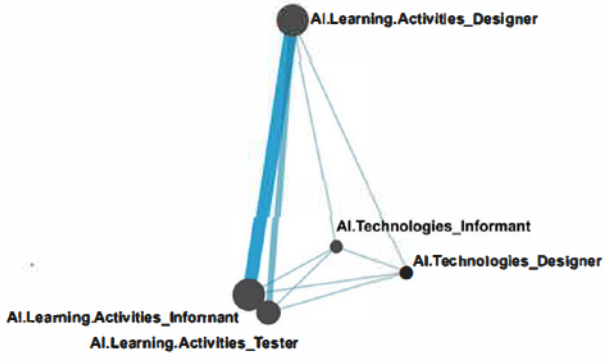

Figure 2. Talia's network.

The results of Cycle Two -Spring 2021 suggest that children primarily acted as informants, testers, designers of AI technologies. Children embodied these roles when they used Google Teachable Machine to build, test, and refine their own machines. During these events, researchers partnered with children and facilitated the activities and reflective discussions. After the activities were completed, researchers conducted interviews with the children to reflect on their machine learning application designs and the other learning activities.

4.2.1. Example: Gina's machine learning application

During Gina's reflective interview, one researcher asked Gina to display her model and share how it worked. Gina explained that she built a machine that could classify colours to be a prototype for teaching young children about their colours (Figure 3). Gina explained that she built her training dataset by searching for photos on Google and then used those photos to train her machine. She stated,

> I took pictures off of Google, different colors, and then I inserted them into the teachable machine area. And then basically, what I did was I took those pictures and I taught the machine by those pictures... So, I took a picture of a black rock, and I put that to the camera.

In this example, Gina embodied the role of a **designer** of AI applications. In order to cultivate a training dataset for classifying different colours, she selected pictures of objects on Google and used the pictures as data to train her model. When she described the process of training the machine, she explained that she 'taught the machine by those pictures', indicating a deliberate design plan for building her classifier. When Gina was asked by the researcher about the challenges she may have encountered while making her teachable machine, she talked about not realising that the material's texture could affect her algorithm. She pointed out that the texture can change how the colour appears and as a result, the machine could misclassify the colour. She stated,

> When I first started making my machine, I didn't really take into question that there might be different textures and colors. So, at first, I just put in solid colors, but then I realized when I put my [black] mask up to the camera that there's multiple different textures and stuff of different color.

As Gina continued reflecting on her AI application, she reviewed her criteria for choosing training data and questioned how broad and diverse her selection criteria were, taking into consideration how texture can affect the colour of an object. She realised the effect of texture on her model when she tested the model using her black, textured face mask, which was of a different texture than black objects in her training dataset.

As a designer, Gina created a model and selected training data based on her initial criteria. However, when assuming the role of a **tester**, she uncovered bias in her design, which led to unanticipated misclassifying of colours. The results of her test prompted her to question the diversity of her training data set. She continued,

> Gina: And so, I realized that you needed to add different feelings to each color. So, for each color, I inserted a different texture. So, for black, I put a black rock. For white, I put paint. For yellow, I put a flower, and so on. So, you could see there's multiple different textures. So, if you put like, my hand up to the camera, you'd be able to notice that my hands not fully flat, because I'm really wrinkly.
>
> Researcher: [laughter] Yeah, we all are wrinkly [holds her hand up]
>
> Gina: Yeah, my hands are really wrinkly! [holds her hand up]

Here, Gina interacts with the researcher in a playful manner, further described how the lack of including texture compelled her to improve her design. She provided another example of texture differences by lifting up her hand and noting that her hand is 'really wrinkly', as opposed to an object that would be 'fully flat'. By acknowledging the potential impact of texture on colour classification, she broadened her selection criteria and improved her training data set by including a diverse range of textures. She provided examples of this diverse range: 'for black, I put a black rock. For white, I put paint. For yellow, I put a flower, and so on ...'

Gina's primary focus was on describing her machine learning application and its functionality. However, Gina did provide some suggestions for improving the design of the educational programme and acted as an **informant** of AI learning activities. For example, when the researcher asked her,

> Okay, if we were to come back in the summer ... what sort of things would you want to work on with us? Would there be anything you're interested in kind of related to that or even just not related to that that you want to know?

Gina excitedly responded in a fast pace,

> Pollution and gardening. Okay, like we could like have a garden that is focused on stopping pollution, like a plant that specifically filters out ... but it's like a plant that connects to like our atmosphere, and spreads

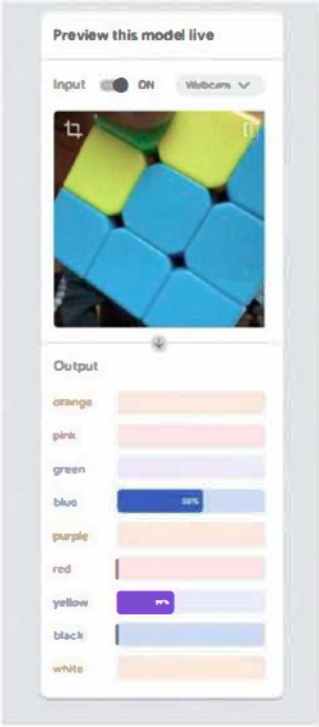

Figure 3. Gina's machine learning model.

> around in that area. So, we can put like the plant–put a pole in the middle that has like lights on it. So, at night-time, like streetlights, but they're not super bright … We can make a 3D model.

Here, Gina suggested a project focused on fighting air pollution by programming lights to support the growth of plants in cities.

In Gina's example, we can see a child embody and connect among the roles of tester, informant, and designer of AI technologies. Visualising her discourse, Gina's network (Figure 4) primarily shows strong connections among testing, informing, and designing AI

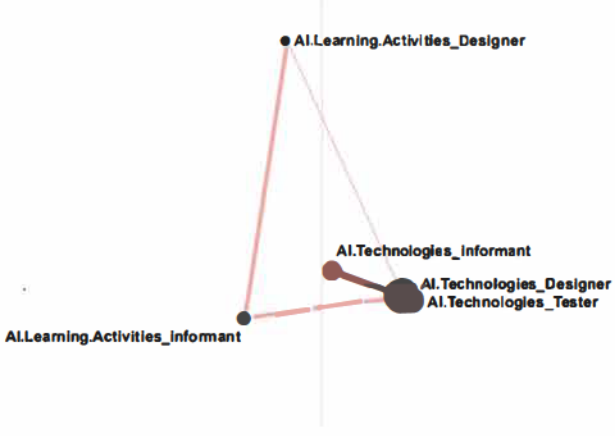

Figure 4. Gina's network.

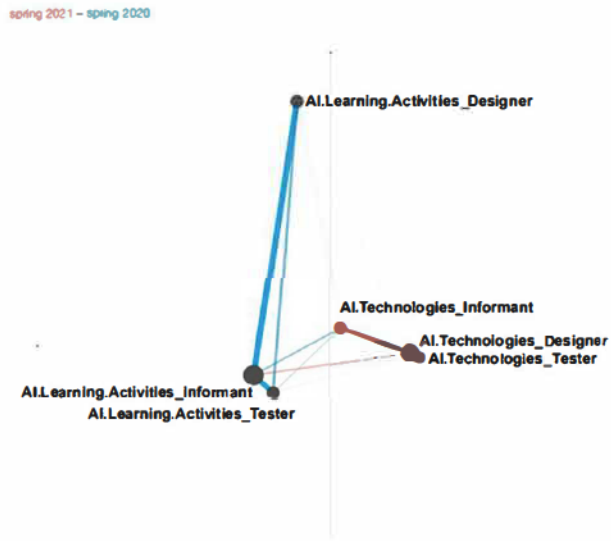

Figure 5. Mean subtracted network comparing Spring 2020 and Spring 2021 connections.

technologies, which reinforces the analysis above. These connections were evident in her descriptions of her machine learning application that could recognise colours but needed refinement and the addition of different textures in her training dataset after she tested it.

4.3. Comparing the two cycles: from designers of AI learning activities to designers of AI technologies

The subtracted network (Figure 5) shows the mathematical difference between the mean weighted networks from Cycle 1-Spring 2020 and Cycle 2-Spring 2021. Each link in the subtracted network is created by subtracting the numeric weights of the Cycle 2 Spring 2021 network from the corresponding links in the Cycle 1 Spring 2020 mean network. If the link in the subtracted network is blue, then the Cycle 1-Spring 2020 children made more connections with those codes. Conversely, if the link in the subtracted network is red, then the Cycle 2-Spring 2021 children make more connections with those codes. Thicker links represent larger differences, and thinner links represent smaller differences.

The subtracted network reveals children in Cycle 1-Spring 2020 made stronger connections between the roles around AI Learning Technologies than children in Cycle 2-Spring 2021. This difference suggests that in the first stages of co-designing a critical machine learning programme, children provided reflective feedback to adult researchers on the design of AI learning activities. In contrast, children in Cycle 2-Spring 2021 made stronger connections between testers, informants, and designers of AI technologies than children in Cycle 1-

Spring 2020. This difference suggests that in the second stages of co-designing a critical machine learning programme, children took a more active design role in building and testing machine learning applications, but less of a role in designing the learning activities.

This result highlights the evolving roles of children in two different cycles of co-designing a critical machine learning programme. In Cycle 1, children were actively discussing and influencing how AI-related learning activities should be structured and improved from their worldviews. While in Cycle 2, children took on an active role in building and testing machine learning applications. However, they were less focused on providing feedback on designing the learning activities themselves. This shift indicates the programme's progression where, over time, the children became more involved in hands-on design and testing of AI technologies and the changing level of involvement of the children in different stages of the co-design process.

The centroid plot (Figure 6) displays the centres of mass (centroids) of the individual children's discourse networks. The blue square represents the mean location of the centroids for Cycle 1-Spring 2020, and the red square represents the mean location of the centroids for Cycle 2-Spring 2021. The dotted lines represent 99% confidence intervals. The Euclidean space is created from a singular value decomposition dimensional reduction and the first two dimensions are shown here, which collectively account for about 67% of the variance in the data. According to the node placement of the codes, we clearly interpreted the positive x-axis as *Informing, Testing, and Designing AI Technologies* and the negative x-axis as *Informing, Testing, and Designing AI Learning Activities*. On the y-axis, children who had network centroid that were more positive on the y-axis made more connections to *Designing AI Learning Activities*. However, the y-axis was more difficult to clearly interpret because there was no significant difference between the two cycles.

Figure 6. The centroid plot showing the centres of mass (centroids) of the individual children's discourse networks.

Note: The green point shows Talia's position on the centroid plot and the orange represents Gina's position.

Along the X axis, a two sample t test assuming unequal variance showed Spring 2020 (mean = −0.68, SD = 0.31, $N = 7$) was statistically significantly different at the alpha = 0.05 level from Spring 2021 (mean = 0.25, SD = 0.54, $N = 19$; $t(18.80) = 5.42^{*}$, $p = 0$, Cohen's d = 1.89). Along the Y axis, a two sample t test assuming unequal variance showed Spring 2020 (mean = 0.26, SD = 0.63, $N = 7$) was *not* statistically significantly different at the alpha = 0.05 level from Spring 2021 (mean = −0.10, SD = 0.26, $N = 19$; $t(6.76) = 1.47$, $p = 0.19$, Cohen's $d = 0.93$).

5. Discussion

Findings in this study suggest that in two participatory design-based research cycles (Spring 2020 and Spring 2021), children embodied different roles of tester, informant, or designer of both *AI learning activities* and *AI technologies*, while at the same time learning computing knowledge and practices. As this research is currently in progress and involves the development of a Critical Machine Learning programme targeted at upper elementary-aged children, the entire programme, including learning activities and AI technologies, is regarded as being in the prototype phase. Therefore, the children participating in our study were perceived as potential testers, informants, or designers, based on the extent of their contribution and engagement throughout the project. While Druin (2002), defined the roles of children from the perspective of designing a new technology with and for children, we have taken a broader approach in the sense that we examine children's involvement in the design of a Critical Machine Learning programme, encompassing both learning activities and technologies. In the initial phase, we introduced a prototype programme with which children in our study interacted, participating in various ways: testing the activities and technologies, providing feedback, or even engaging in some aspects of designing the activities or technologies. Against this background, we define the roles of testers, informants, and designers in a manner that bears similarities to, yet also slightly diverges from, Druin's established definitions (refer to Table 4 for details). In our study, we define the role of a tester as when children interact with pre-developed learning activities and AI technologies, such as Scratch AI, programming AI robots, or Teachable Machine models, and subsequently share their experiences. Their feedback is basic, focusing on whether or not they enjoyed the experience.

In the informant role, children engage more deeply than merely using technology. They interact with researchers through conversations or sketching activities to propose enhancements to the learning activities or AI technologies they used. In this role, children are primarily focused on offering insights or ideas that could improve their learning or user experience, based on their observations and interactions with the activities or technologies.

While Druin's definition of the designer's role encompasses aspects of both testers and informants with an emphasis on children's involvement in the entire process of collectively designing a specific technology (Druin 2002), our study recognises but slightly adapts this definition. We specifically define designers as children who engage in the creative process of designing and building AI digital technologies and/or learning activities. This role includes discussing, sketching, or demonstrating the design and building processes, as well as testing the AI technologies or learning activities they create. This involves a more hands on engagement, including ideation, reflection, brainstorming, and developing prototypes of AI technology and learning activities.

5.1. Visualising the PDR process and children's dynamic roles

In the first cycle (Spring, 2020), through a critical and situated constructivist lens (Kafai, Proctor, and Lui 2019), researchers designed preliminary activities to engage children in learning about AI and machine learning content. We encouraged children to reify their thinking through a situated and critical lens by creating 'objects-to-think-with' such as building a Google Teachable Machine that aligned with their own interests and identifying bias in their training datasets. After the implementation, we analyzed the reflective interviews and observational field notes using ENA (Shaffer 2017) to visualise each child's discourse network. We provided an example of one child from each cycle to allow for a micro-analysis of discourse, unpacking the language that the child used. A weighted network supported the micro-level analysis by providing a holistic visualisation of Talia and Gina's discourse and how they connected across the three roles and the two contexts. Correspondingly, ENA provided a macro-level analysis of all the child participants by creating a fixed mathematical space and plotting the centroids of all the children's discourse networks. The centroid analysis paired with the statistically significant result between the two cycles provides a form of validity and suggests theoretical saturation of the data and claims being made in this study about the shift of roles over time (Arastoopour Irgens and Eagan 2022c; Shaffer 2017).

In our analysis, we discovered that children in Cycle One – Spring 2020, mainly played the roles of tester, informant, and designer of *AI learning activities*. In cycle two, we improved the programme based on researcher observations of children testing the activities, direct feedback from the children, and reflective interviews in which children and researchers refined and co-designed activities from Cycle One – Spring 2020. Our findings revealed a shift from children as designers of AI *learning activities* to children as designers of AI *technologies*.

Like studies conducted by Druin (2002) and Yip and Lee (2018), Yip, Lee, and Lee (2020), our research reveals that the roles we've identified are dynamic rather than static. The embodiment of these roles evolves over time within the context of designing technologies and learning activities. This indicates that as children engage with the design process, their roles as testers, informants, or designers are not predetermined or rigid; instead, they shift and develop in response to the evolving nature of the project and the children's growing experience and engagement. In these prior studies, researchers used single case studies and descriptive qualitative research methods to analyze the data. Our current study extends methodological work in the Child-Computer Interaction field in two ways. First, given that children embody dynamic and intersecting roles in co-design, quantitative ethnography tools such as ENA provide a way to visualise these *intersecting* roles using the same, rich qualitative data from interviews, observations, and artifacts from prior studies. While statistics are used to measure saturation and create visualisations, the heart of quantitative ethnography around the creation of a 'thick description' of what people do and why they do it (Arastoopour Irgens and Eagan 2022c). The links in a discourse network provide a summary representation of the discourse of one or more children to see how their roles connect and intersect during design processes, which has not been done before. Second, tools such as ENA also provide a way to visualise *dynamic* roles in design and how these roles shift over time. The subtracted network visualisation revealed how roles changed from 2020 to 2021 in one summary representation, which again has not been done in participatory design with children. These methodological advances mirror claims in the field of quantitative ethnography around how such network visualisations can reveal stories about vulnerable populations that have not been told before using traditional qualitative methods (Arastoopour Irgens 2019) and how measuring connections in discourse can provide alternative, meaningful interpretations of qualitative data (Collier, Ruis, and Shaffer 2016).

According to our quantitative ethnography analysis, there are several design changes that facilitated the shift of roles from designers of AI *learning activities* to children as designers of AI *technologies*. First, we refined the activities in Cycle Two – Spring 2021 to include activities that progressed in complexity. For example, children followed a structured cat–dog activity to train a Google Teachable Machine and investigate bias before creating their own machines. This change provided a foundation for Gina and other children in Cycle Two to be prepared to design their own machine learning technologies. Second, we implemented Talia's ideas about the physical space and variety of stations. We also included more food and snacks as she suggested. This change provided space for children to process the complexities around algorithm bias and socialise with their peers and adult facilitators as they designed. Third, based on our observations, we realised children did not see the consequences of their machine learning applications in the physical world. Although children explored algorithm bias through the Google Image Search activity and Coded Bias discussion, they were missing the creation of an object to reify such ideas. Thus, we introduced programmable robots that responded to children's classifiers in cycle two. In turn, in cycle two, children focused more on informing, testing, and designing the AI technologies themselves, rather than the activities. This finding aligns with existing literature that children are not passive or homogeneous users, but active and diverse participants in the design and evaluation of technology (Druin 2002). Furthermore, children's roles and perspectives can change over time, depending on the nature and goals of the project, the methods and tools used, and the level of involvement and feedback children get. Recognising the dynamic nature of children's roles in Child-Computer Interaction (CCI) Communities highlights the importance of more inclusive design processes. The implication is CCI researchers and practitioners need to be flexible and adaptive in their approaches and use methods that can capture the dynamic and evolving nature of children's roles and experiences (Jones and Bubb 2021). Choosing appropriate techniques and tools that match the children's abilities, interests, and preferences can capture and accommodate the shifting nature of children's roles in designing technology programmes. For example, using low-fidelity prototypes, storyboards, sketches, or tangible objects can facilitate children's expression and communication of their ideas as demonstrated in Yip et al. 2013. Also, providing scaffolding and support through adult facilitators or mentors can guide, encourage, and challenge children to explore and experiment with technology or learning activities (Clark 2010; Druin 2005; Frauenberger, Good, and Keay-Bright 2011; Jones and Bubb 2021; Theodoropoulos 2022).

We would like to continue this work as we continue to refine the programme with different populations of children and discover whether this trend towards a focus on designing technologies continues or if we see a pivot back to designing learning activities again.

5.2. Slow research: breaking the paradox and taking our time

In Cycle One – Spring 2020, children's focus on designing AI learning activities was likely because there was a misalignment between the researcher's vision for the programme and the children's vision for the programme. Although the researchers grounded the design of the educational programme in learning theory and empirical studies on AI education, children's voices were not included in the initial design of the programme in the first cycle. And when children's voices are not included in curriculum design, their interests and lived experiences are likely not reflected in the activities and content (Bron and Veugelers 2014; Clauhs and Cremata 2020; Walker 2015). However, we discovered that this cycle of initial design and testing is necessary for breaking the paradox of engaging children in co-design of curricula when they have not yet learned the disciplinary content within the curricula (Bonsignore et al. 2013). When co-designing learning activities with children, researchers must start with a best guess of what will motivate their population to learn and engage based on existing theory and empirical work. In this study, we leveraged design-based research principles of building learning theory through experimentation (Barab et al. 2004) and participatory design research principles of equitably partnering with participants (Bang and Vossoughi 2016). We prioritised building trust with our child participants (Cumbo 2019; Cumbo and Selwyn 2022) to establish equitable and multifaceted relations (Yip et al. 2017) and to improve the quality of the design and research. By involving children as our primary partners, we spent three years (1) designing initial learning activities, (2) building relationships with children and staff, (3) refining activities as we cultivated relationships and learned about the children's interests and lived experiences, (4) testing activities and refined activities during implementations based on observations in the field, (5) reflecting with children after a full cycle of implementation, and (6) refining activities based data collected in cycle one in preparation for cycle two. Then, we repeated these six steps for cycle two. These activities occurred over two

different cycles of iteration with the children. This work will continue and involves refining the programme based on the analysis of cycle two data in preparation for cycle three. We will continue to refine the activities, work with different populations of children, and continue to build learning theory.

In cycle three of co-designing the programme, we have begun to explore more active role-play as children engage in curricula activities. Direct observation and feedback from children in cycle two suggest that while children wanted more technology-driven activities, they tended to be more engaged when the activities were narrative-driven. Thus, further design of the programme is proposed to be a fully narrative-driven technology-based activity immersed in role play (Adisa et al. 2023).

All in all, such cycles of PDR with children as co-designers that foreground relationships, trust-building, and reflexivity take a significant amount of time. But in order to involve children in the design of their own learning experiences in computing education and break the paradox of informed participation, researchers must be prepared for year-long cycles of design and to take their time conducting research. Thus, we propose to slow down participatory design-based research when co-designing learning experiences that contains a core technology design component with and for children. Similar to arguments made from other scholars who work with children (Horton and Kraftl 2005; Millei and Rautio 2017), our proposal for *slow research* in PDR acknowledges that merging theory building, improving problems of practice, and privileging relational work will extend the research timeline. For example, as noted above, researchers spent several days with children and staff where there was no data collection. Rather, the focus was to play together with technologies, play outside, work on homework, eat snacks, and have conversations. Throughout the programme, adults and children were playful and laughed together often. For example, in Gina's interview, she referred to her hand as wrinkly when she was testing how her colour classifier machine could recognise colours on textured objects. Because of their rapport, the researcher found this comment humorous, laughed, and she and Gina raised their 'wrinkly hands'. Thus, we believe that prioritising relational work between adult researchers and children sets the foundation for effective, trusting co-design work in the future.

6. Conclusion

In this project, we allow children to integrate their lived experiences as they test, inform, and design both learning activities and technologies. This study provides a visual analysis of the types of roles children play over time in participatory design of new technologies and activities for learning. By collecting and responding to observational notes and reflective interviews with children, we refined the learning activities and saw a shift in roles from designers of learning activities to designers of technologies. Including children in the design of their learning environments provides opportunities for more relevant, engaging, and equitable learning experiences that extend their skillsets (Cumbo and Selwyn 2022). We encourage researchers to engage in slow research to allow children to play significant and shifting roles in the design of their learning environments. For future work, this research could be significantly enhanced by a deeper exploration of the diversity among child participants. Investigating and understanding the varied backgrounds, experiences, and perspectives of these children can provide richer, more nuanced insights into the co-design process.

Acknowledgement

This work is funded in part by the National Science Foundation (ECR-2024965, DRL-2238712) and the Office of the Associate Dean for Research in the College of Education at Clemson University. The opinions, findings, and conclusions do not reflect the views of the funding agencies, cooperating institutions, or other individuals.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work is funded in part by the National Science Foundation (ECR-2024965, DRL-2238712) and the Office of the Associate Dean for Research in the College of Education at Clemson University.

References

Adisa, I. O., I. Thompson, T. Famaye, D. Sistla, C. S. Bailey, K. Mulholland, A. Fecher, C. M. Lancaster, and G. Arastoopour Irgens. 2023. "S.P.O.T: A Game-based Application for Fostering Critical Machine Learning Literacy Among Children." In *Proceedings of the 22nd Annual ACM Interaction Design and Children Conference*, 507–511. https://doi.org/10.1145/3585088.3593884.

Ahn, J., M. Subramaniam, E. Bonsignore, A. Pellicone, A. Waugh, and J. Yip. 2014. *I Want to be a Game Designer or Scientist: Connected Learning and Developing Identities with Urban, African-American Youth*. https://repository.isls.org//handle/1/1177.

Alves-Oliveira, P., P. Arriaga, A. Paiva, and G. Hoffman. 2021. "Children as Robot Designers." In *Proceedings of the 2021 ACM/IEEE International Conference on Human-Robot*

Interaction, 399–408. https://doi.org/10.1145/3434073.3444650.

Arastoopour Irgens, G. 2019. "Quantitative Ethnography Across Domains: Where We are and Where We are Going." In *International Conference for Quantitative Ethnography*, University of Wisconsin, Madison, WI. https://mediaspace.wisc.edu/media/1_wc2vypki.

Arastoopour Irgens, G. A., I. Adisa, C. Bailey, and H. V. Quesada. 2022b. "Designing with and for Youth: A Participatory Design Research Approach for Critical Machine Learning Education." *Educational Technology & Society* 25 (4): 126–141. https://www.jstor.org/stable/48695986.

Arastoopour Irgens, G., and B. Eagan. 2022c. "Fundamentals and Foundations of Quantitative Ethnography." In *Fourth International Conference, ICQE 2021*, International Society for Quantitative Ethnography, Copenhagen, Denmark.

Arastoopour Irgens, G., H. Vega, I. Adisa, and C. Bailey. 2022a. "Characterizing Children's Conceptual Knowledge and Computational Practices in a Critical Machine Learning Educational Program." *International Journal of Child-Computer Interaction* 34:100541. https://doi.org/10.1016/j.ijcci.2022.100541.

Bang, M., and S. Vossoughi. 2016. "Participatory Design Research and Educational Justice: Studying Learning and Relations Within Social Change Making." *Cognition and Instruction* 34 (3): 173–193. https://doi.org/10.1080/07370008.2016.1181879.

Barab, S. A., M. K. Thomas, T. Dodge, K. Squire, and M. Newell. 2004. "Critical Design Ethnography: Designing for Change." *Anthropology & Education Quarterly* 35 (2): 254–268. https://doi.org/10.1525/aeq.2004.35.2.254.

Bonsignore, E., J. Ahn, T. Clegg, M. L. Guha, J. C. Yip, and A. Druin. 2013. *Embedding Participatory Design into Designs for Learning: An Untapped Interdisciplinary Resource?*

Bowman, D., Z. Swiecki, Z. Cai, Y. Wang, B. Eagan, J. Linderoth, and D. W. Shaffer. 2021. "The Mathematical Foundations of Epistemic Network Analysis." In *Advances in Quantitative Ethnography*, edited by A. R. Ruis and S. B. Lee, 91–105. Springer International Publishing. https://doi.org/10.1007/978-3-030-67788-6_7.

Bron, J., and W. Veugelers. 2014. "Why We Need to Involve Our Students in Curriculum Design: Five Arguments for Student Voice." *Curriculum and Teaching Dialogue* 16 (1–2): 125–140.

Brooman, S., S. Darwent, and A. Pimor. 2015. "The Student Voice in Higher Education Curriculum Design: Is There Value in Listening?" *Innovations in Education and Teaching International* 52 (6): 663–674. https://doi.org/10.1080/14703297.2014.910128.

Brown, A. L. 1992. "Design Experiments: Theoretical and Methodological Challenges in Creating Complex Interventions in Classroom Settings." *Journal of the Learning Sciences* 2 (2): 141–178. https://doi.org/10.1207/s15327809jls0202_2.

Buddemeyer, A., J. Nwogu, J. Solyst, E. Walker, T. Nkrumah, A. Ogan, L. Hatley, and A. Stewart. 2022. "Unwritten Magic: Participatory Design of AI Dialogue to Empower Marginalized Voices." In *Conference on Information Technology for Social Good*, 366–372. https://doi.org/10.1145/3524458.3547119.

Carey, P. 2013. "Student as Co-producer in a Marketised Higher Education System: A Case Study of Students' Experience of Participation in Curriculum Design." *Innovations in Education & Teaching International* 50 (3): 250–260. https://doi.org/10.1080/14703297.2013.796714.

Charmaz, K. 2004. "Premises, Principles, and Practices in Qualitative Research: Revisiting the Foundations." *Qualitative Health Research* 14 (7): 976–993. https://doi.org/10.1177/1049732304266795.

Clark, A. 2010. "Young Children as Protagonists and the Role of Participatory, Visual Methods in Engaging Multiple Perspectives." *American Journal of Community Psychology* 46 (1–2): 115–123. https://doi.org/10.1007/s10464-010-9332-y.

Clauhs, M., and R. Cremata. 2020. "Student Voice and Choice in Modern Band Curriculum Development." *Journal of Popular Music Education* 4 (1): 101–116. https://doi.org/10.1386/jpme_00016_1.

Cobb, P., J. Confrey, A. diSessa, R. Lehrer, and L. Schauble. 2003. "Design Experiments in Educational Research." *Educational Researcher* 32 (1): 9–13. https://doi.org/10.3102/0013189X032001009.

Coenraad, M., J. Palmer, D. Franklin, and D. Weintrop. 2019. "Utilizing Participatory Design to Develop a Culturally Relevant Computer Science Curriculum." In *Proceedings of the 50th ACM Technical Symposium on Computer Science Education*, 1261. https://doi.org/10.1145/3287324.3293803.

Collier, W., A. Ruis, and D. W. Shaffer. 2016. *Local Versus Global Connection Making in Discourse*. https://repository.isls.org//handle/1/145.

Cumbo, B. J. 2019. "Child Participation Beyond the Adult Realm: Participatory Design in Nature-play Contexts." Thesis. https://opus.lib.uts.edu.au/handle/10453/140231.

Cumbo, B., and N. Selwyn. 2022. "Using Participatory Design Approaches in Educational Research." *International Journal of Research & Method in Education* 45 (1): 60–72. https://doi.org/10.1080/1743727X.2021.1902981.

Desportes, K., K. McDermott, Y. Bergner, and W. Payne. 2022. "'Go[ing] Hard … as a Woman of Color': A Case Study Examining Identity Work within a Performative Dance and Computing Learning Environment." *ACM Transactions on Computing Education* 22 (4): 49:1–49:29. https://doi.org/10.1145/3531000.

Dietz, G., J. Han, H. Gweon, and J. A. Landay. 2021. "Design Guidelines for Early Childhood Computer Science Education Tools." In *Design Thinking Research: Interrogating the Doing*, edited by C. Meinel and L. Leifer, 291–306. Springer International Publishing. https://doi.org/10.1007/978-3-030-62037-0_13.

diSessa, A. A., and P. Cobb. 2004. "Ontological Innovation and the Role of Theory in Design Experiments." *The Journal of the Learning Sciences* 13 (1): 77–103. https://doi.org/10.1207/s15327809jls1301_4. https://www.jstor.org/stable/1466933.

Druga, S., R. Williams, C. Breazeal, and M. Resnick. 2017. "*Hey Google is it ok if I eat you?" Initial explorations in child-agent interaction*, 595–600.

Druin, A. 1997. "Kids are not 'Adults-in-waiting'." *ACM SIGCHI Bulletin* 29 (3): 18–19. https://doi.org/10.1145/264853.264861.

Druin, A. 2002. "The Role of Children in the Design of New Technology." *Behaviour and Information Technology* 21 (1): 1–25.

Druin, A. 2005. "What Children can Teach us: Developing Digital Libraries for Children with Children." *The Library Quarterly* 75 (1): 20–41. https://doi.org/10.1086/428691.

Druin, A., B. B. Bederson, J. P. Hourcade, L. Sherman, G. Revelle, M. Platner, and S. Weng. 2003. "Designing a Digital Library for Young Children: An Intergenerational Partnership." In *The Craft of Information Visualization*, 178–185. Elsevier. https://doi.org/10.1016/B978-155860915-0/50023-8.

Durl, J., T. Dietrich, B. Williams, and S. Rundle-Thiele. 2022. "Integrating Student and Teacher Insights to a School-based Alcohol Program Through Co-design." *Health Promotion International* 37 (2): daab167. https://doi.org/10.1093/heapro/daab167.

Eden, H. 2002. *Getting in on the (Inter)Action: Exploring Affordances for Collaborative Learning in a Context of Informed Participation*. https://repository.isls.org//handle/1/3802.

Fails, J. A., D. kumar Ratakonda, N. Koren, S. Elsayed-Ali, E. Bonsignore, and J. Yip. 2022. "Pushing Boundaries of Co-design by Going Online: Lessons Learned and Reflections from Three Perspectives." *International Journal of Child-Computer Interaction* 33:100476. https://doi.org/10.1016/j.ijcci.2022.100476.

Frauenberger, C., J. Good, and W. Keay-Bright. 2011. "Designing Technology for Children with Special Needs: Bridging Perspectives through Participatory Design." *CoDesign* 7 (1): 1–28. https://doi.org/10.1080/15710882.2011.587013.

Garzotto, F. 2008. "Broadening Children's Involvement as Design Partners: From Technology to." In *Proceedings of the 7th International Conference on Interaction Design and Children*, 186–193. https://doi.org/10.1145/1463689.1463755.

Gee, J. P. 2014. *An Introduction to Discourse Analysis: Theory and Method*. United Kingdom: Taylor & Francis.

Gillett-Swan, J., A. Winter, and A. Radovic. 2023. "Engaging with Children and Young People about their School Experience: Co-Designing a 'Talking Tree' Research Tool to Investigate Why School Works for Some Students, But not Others." *Journal of Participatory Research Methods* 4 (2). https://doi.org/10.35844/001c.75239.

Guha, M. L., A. Druin, and J. A. Fails. 2013. "Cooperative Inquiry Revisited: Reflections of the Past and Guidelines for the Future of Intergenerational co-Design." *International Journal of Child-Computer Interaction* 1 (1): 14–23. https://doi.org/10.1016/j.ijcci.2012.08.003.

Hoadley, C. 2002. *Creating Context: Design-based Research in Creating and Understanding CSCL*, 453–462. https://doi.org/10.3115/1658616.1658679.

Holbert, N., M. Dando, and I. Correa. 2020. "Afrofuturism as Critical Constructionist Design: Building Futures from the Past and Present." *Learning, Media and Technology* 45 (4): 328–344. https://doi.org/10.1080/17439884.2020.1754237.

Holbert, N., and U. Wilensky. 2019. "Designing Educational Video Games to be Objects-to-Think-with." *Journal of the Learning Sciences* 28 (1): 32–72. https://doi.org/10.1080/10508406.2018.1487302.

Horton, J., and P. Kraftl. 2005. "For More-than-usefulness: Six Overlapping Points about Children's Geographies." *Children's Geographies* 3 (2): 131–143. https://doi.org/10.1080/14733280500161503.

Hussain, S. 2010. "Empowering Marginalised Children in Developing Countries through Participatory Design Processes." *CoDesign* 6 (2): 99–117. https://doi.org/10.1080/15710882.2010.499467.

Iversen, O. S., R. C. Smith, and C. Dindler. 2017. "Child as Protagonist: Expanding the Role of Children in Participatory Design." In *Proceedings of the 2017 Conference on Interaction Design and Children*, 27–37. https://doi.org/10.1145/3078072.3079725.

Jones, M.-A., and S. Bubb. 2021. "Student Voice to Improve Schools: Perspectives from Students, Teachers and Leaders in 'Perfect' Conditions." *Improving Schools* 24 (3): 233–244. https://doi.org/10.1177/1365480219901064.

Kafai, Y. B., C. Proctor, and D. A. Lui. 2019. Framing Computational Thinking for Computational Literacies in K-12 Education." In *Proceedings of the Weizenbaum Conference 2019 "Challenges of Digital Inequality—Digital Education, Digital Work, Digital Life"*, 6. https://doi.org/10.34669/wi.cp/2.21.

Kafai, Y. B., and M. Resnick, eds. 1996. *Constructionism in Practice: Designing, Thinking, and Learning in A Digital World*. 1st ed. Newyork: Routledge.

Kankaanranta, M., S. Mehtälä, M. Hankala, O. Merjovaara, and R. Rousi. 2021. "Children's Conceptions of Mental Well-being and Ideas for its Promotion Through Digital Environments." *International Journal of Child-Computer Interaction* 27:100242. https://doi.org/10.1016/j.ijcci.2020.100242.

Leat, D., and A. Reid. 2012. "Exploring the Role of Student Researchers in the Process of Curriculum Development." *Curriculum Journal* 23 (2): 189–205. https://doi.org/10.1080/09585176.2012.678691.

Marquart, C. L., C. Hinojosa, Z. Swiecki, B. Eagan, and D. W. Shaffer. 2018. *Epistemic Network Analysis (Version 1.7.0)[Software]*. App.Epistemicnetwork.Org.

Millei, Z., and P. Rautio. 2017. "'Overspills' of Research with Children: An Argument for Slow Research." *Children's Geographies* 15 (4): 466–477. https://doi.org/10.1080/14733285.2016.1277182.

Morrison, C., E. Cutrell, M. Grayson, A. Thieme, A. Taylor, G. Roumen, C. Longden, S. Tschiatschek, R. Faia Marques, and A. Sellen. 2021. "Social Sensemaking with AI: Designing an Open-ended AI Experience with a Blind Child." In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3411764.3445290.

Nissinen, E., P. Korhonen, V. Vellonen, E. Kärnä, and M. Tukiainen. 2012. *Children with Special Needs as Evaluators of Technologies*, 1356–1365. https://www.learntechlib.org/primary/p/40926/.

O'Neil, C. 2017. *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. New York: Crown.

O'Reilly, K. 2012. *Ethnographic Methods*. New York: Routledge.

Ottenbreit-Leftwich, A., K. Glazewski, M. Jeon, K. Jantaraweragul, C. E. Hmelo-Silver, A. Scribner, S. Lee, B. Mott, and J. Lester. 2023. "Lessons Learned for AI Education with Elementary Students and Teachers." *International Journal of Artificial Intelligence in Education*

33 (2): 267–289. https://doi.org/10.1007/s40593-022-00304-3.

Papert, S. 1980. *Mindstorms: Children, Computers, and Powerful Ideas*. United States: Basic Books.

Papert, S., and I. Harel. 1991. " Situating constructionism." *Constructionism* 36 (2): 1–11.

Philip, T. M., M. Bang, and K. Jackson. 2018. "Articulating the 'How,' the 'For What,' the 'For Whom,' and the 'With Whom' in Concert: A Call to Broaden the Benchmarks of Our Scholarship." *Cognition and Instruction* 36 (2): 83–88. https://doi.org/10.1080/07370008.2018.1413530.

Pires, A. C., E. Bakala, F. González-Perilli, G. Sansone, B. Fleischer, S. Marichal, and T. Guerreiro. 2022. "Learning Maths with a Tangible User Interface: Lessons Learned through Participatory Design with Children with Visual Impairments and their Educators." *International Journal of Child-Computer Interaction* 32:100382. https://doi.org/10.1016/j.ijcci.2021.100382.

Plummer, E. C., A. Stornaiuolo, G.-G.-S. So-Qui-Li I, J. Lott, C. L. Marrero, D. Z. McLaine, D. Murray-Scott, et al. 2019. "Participatory Ethnography: Developing a High School Writing Center in Partnership." *Penn GSE Perspectives on Urban Education* 16 (1). https://eric.ed.gov/?id=EJ1222653.

Roulston, K. 2010. *Reflective Interviewing: A Guide to Theory and Practice*, 1–216. London: Sage.

Saldana, J. 2021. "The Coding Manual for Qualitative Researchers." *The Coding Manual for Qualitative Researchers*, 1–440. https://www.torrossa.com/en/resources/an/5018667.

Searle, K. A., and Y. B. Kafai. 2015. "Boys' Needlework: Understanding Gendered and Indigenous Perspectives on Computing and Crafting with Electronic Textiles." In *Proceedings of the Eleventh Annual International Conference on International Computing Education Research*, 31–39. https://doi.org/10.1145/2787622.2787724.

Shaffer, D. W. 2017. *Quantitative Ethnography*. Madison, WI: Cathcart Press.

Shaffer, D. W. 2018. "Epistemic Network Analysis: Understanding Learning by Using Big Data for Thick Description." In *International Handbook of the Learning Sciences*, 520–531. New York: Routledge.

Shaffer, D. W., W. Collier, and A. R. Ruis. 2016. "A Tutorial on Epistemic Network Analysis: Analyzing the Structure of Connections in Cognitive, Social, and Interaction Data." *Journal of Learning Analytics* 3 (3): Article 3. https://doi.org/10.18608/jla.2016.33.3.

Siebert-Evenstone, A. L., G. A. Irgens, W. Collier, Z. Swiecki, A. R. Ruis, and D. W. Shaffer. 2017. "In Search of Conversational Grain Size: Modeling Semantic Structure Using Moving Stanza Windows." *Journal of Learning Analytics* 4 (3): Article 3. https://doi.org/10.18608/jla.2017.43.7.

Speer, S., E. Hamner, M. Tasota, L. Zito, and S. K. Byrne-Houser. 2021. "MindfulNest: Strengthening Emotion Regulation with Tangible User Interfaces." In *Proceedings of the 2021 International Conference on Multimodal Interaction*, 103–111. https://doi.org/10.1145/3462244.3479917.

Stålberg, A. 2018. "Facilitating Participation: A Joint Use of an Interactive Technology as a Facilitator in Healthcare Situations." In *4th PNAE Congress on Paediatric Nursing*, Athens, Greece, 1–2 June 2018.

Theodoropoulos, A. 2022. "Participatory Design and Participatory Debugging: Listening to Students to Improve Computational Thinking by Creating Games." *International Journal of Child-Computer Interaction* 34:100525. https://doi.org/10.1016/j.ijcci.2022.100525.

Vakil, S., M. McKinney de Royston, N. Suad Nasir, and B. Kirshner. 2016. "Rethinking Race and Power in Design-based Research: Reflections from the Field." *Cognition and Instruction* 34 (3): 194–209. https://doi.org/10.1080/07370008.2016.1169817.

Vartiainen, H., M. Tedre, and T. Valtonen. 2020. "Learning Machine Learning with Very Young Children: Who is Teaching Whom?" *International Journal of Child-Computer Interaction* 25:100182. https://doi.org/10.1016/j.ijcci.2020.100182.

Walker, J. 2015. "Student Voice in Curriculum Development: Joanne Walker Looks at Pupil Influence on the Teaching of IGCSE Global Perspectives." *IS International School* 17 (2): 35+. Gale OneFile: Educator's Reference Complete. https://link.gale.com/apps/doc/A609836275/PROF?u=clemsonu_main&sid=bookmark-PROF&xid=7e4b8518.

Walsh, G., and E. Foss. 2015. "A Case for Intergenerational Distributed Co-design: The Online Kidsteam Example." In *IDC '15, Proceedings of the 14th International Conference on Interaction Design and Children*, 99–108. Boston, MA: Association for Computing Machinery. https://doi.org/10.1145/2771839.2771850.

Wilensky, U. 1991. *Abstract meditations on the Concrete and Concrete Implications for Mathematics Education*. Cambridge, MA: Epistemology and Learning Group, MIT Media Laboratory.

Wilensky, U., and K. Reisman. 2006. "Thinking Like a Wolf, a Sheep, or a Firefly: Learning Biology through Constructing and Testing Computational Theories—An Embodied Modeling Approach." *Cognition and Instruction* 24 (2): 171–209. https://doi.org/10.1207/s1532690xci2402_1.

Williams, R., and C. Breazeal. 2020. *How to Train Your Robot: A Middle School AI and Ethics Curriculum*.

Yip, J., T. Clegg, E. Bonsignore, H. Gelderblom, E. Rhodes, and A. Druin. 2013. "Brownies or Bags-of-stuff? Domain Expertise in Cooperative Inquiry with Children." In *Proceedings of the 12th International Conference on Interaction Design and Children*, 201–210. https://doi.org/10.1145/2485760.2485763.

Yip, J. C., and K. J. Lee. 2018. "The Design of Digital Learning Activities for Libraries through Participatory Design." In *Reconceptualizing Libraries: Perspectives from the Information and the Learning Sciences*, edited by V. Lee and A. Phillips, 219–232. New York, USA: Routledge.

Yip, J. C., K. J. Lee, and J. H. Lee. 2020. "Design Partnerships for Participatory Librarianship: A Conceptual Model for Understanding Librarians co Designing with Digital Youth." *Journal of the Association for Information Science and Technology* 71 (10): 1242–1256. https://doi.org/10.1002/asi.24320.

Yip, J. C., K. Sobel, C. Pitt, K. J. Lee, S. Chen, K. Nasu, and L. R. Pina. 2017. "Examining Adult-child Interactions in Intergenerational Participatory Design." In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 5742–5754. https://doi.org/10.1145/3025453.3025787.