

# Incorporating Young Children's Values Through Laddering Methodology: Examples from Early Literacy and AI

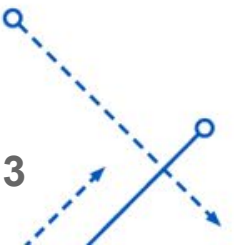
Xintian Tu-Shea<sup>1</sup>, Chris Hoadley<sup>1</sup>, Qingxiao Zheng<sup>1</sup>, Jinjun Xiong<sup>2</sup>

<sup>1</sup>University at Buffalo, <sup>2</sup>The University of Texas at San Antonio

# INTRODUCTION

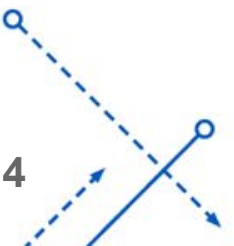
## What is a Laddering Interview?

A laddering interview helps researchers uncover why users value certain design features by moving from concrete experiences toward deeper motivations. (Gutman, 1982)



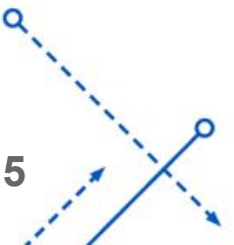
# Why Laddering Interview for Young Children and AI Literacy?

- Design-Based Research (DBR) plays a major role in designing and refining technology-enhanced learning environments
- DBR supports iterative refinement of design conjectures and learning experiences
- However, there is still a methodological gap at the earliest stages:
  - before conjectures are formed
  - before iterative refinement begins

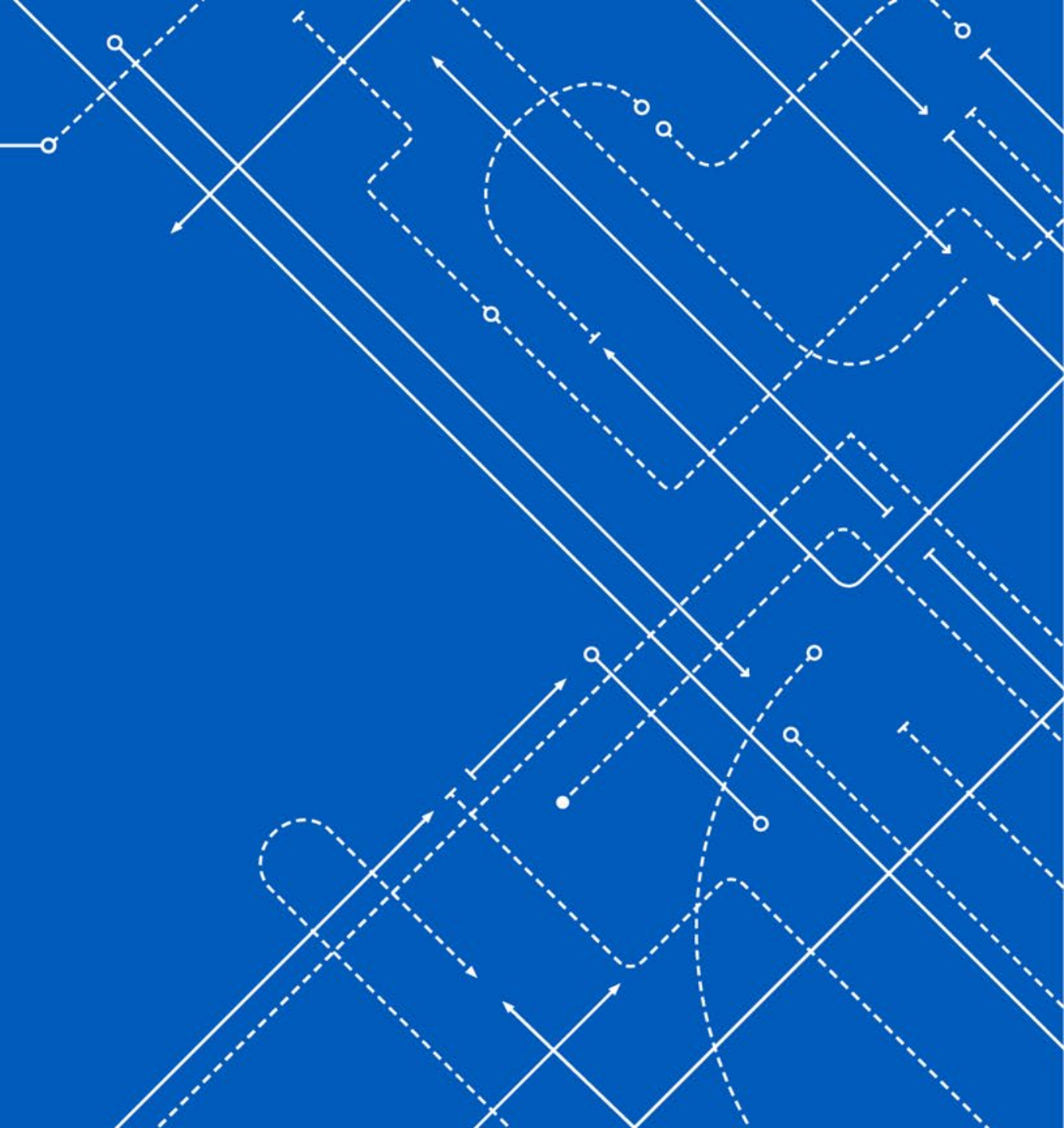


## Existing Approaches and Challenges

- Needs analysis often focuses on predefined competencies or learning outcomes
- Participatory and co-design methods have been adapted for older children, but remain difficult with younger children
- **Young children often struggle to explicitly articulate: preferences, reasoning, underlying values**



# METHODS



# Laddering Interviews and the ACV framework

**Attribute:** Observable feature or characteristic of a system

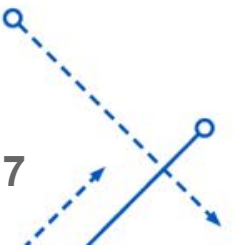
Example: avatar appearance

**Consequence:** Immediate experience, feeling, or outcome resulting from the attribute

Example: “It helps me read better”

**Value:** Underlying personal meaning or motivation

Example: competence



# Applying Laddering with Young Children

## Design Principles Adapted from Zaman 2008

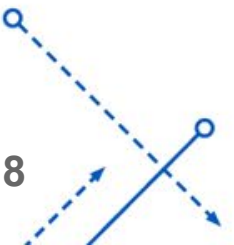
### 1. Provide Concrete Experiences

Young children interacted with target prototypes before interviews.

### 2. Iterative “Why” Probing

Interviewers repeatedly asked:

- “Why do you like that?”
- “Why does that matter?”



# Laddering interview 1: Young children's perspective towards AI-generated Avatars

- Explored young children's perspectives on three AI-generated reading avatars: self-avatar, teacher avatar, and dog avatar

**Figure 1**

*AI-generated avatars. From left to right: participant's selfie, AI-generated self-avatar, teacher avatar, and dog avatar.*



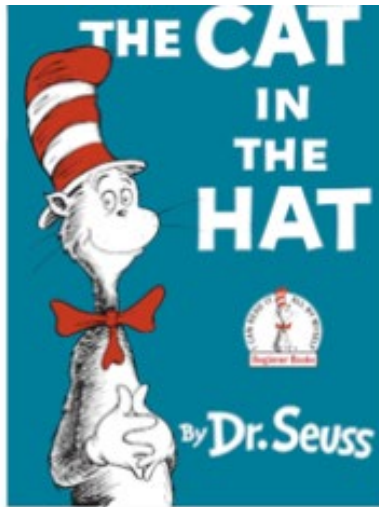
# Laddering interview 1: Young children's perspective towards AI-generated Avatars

- Children (5-10 years old) interacted with each avatar reading aloud and participated in laddering interviews about their experiences, preferences, and future learning use

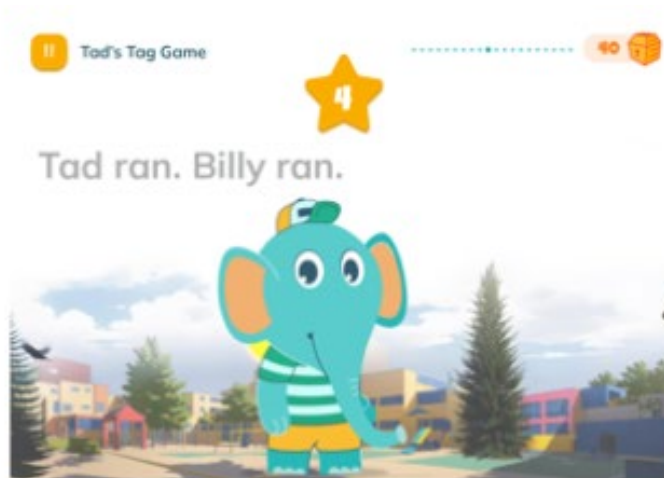


# Laddering interview 2: Young children's broader understanding of AI reading tools

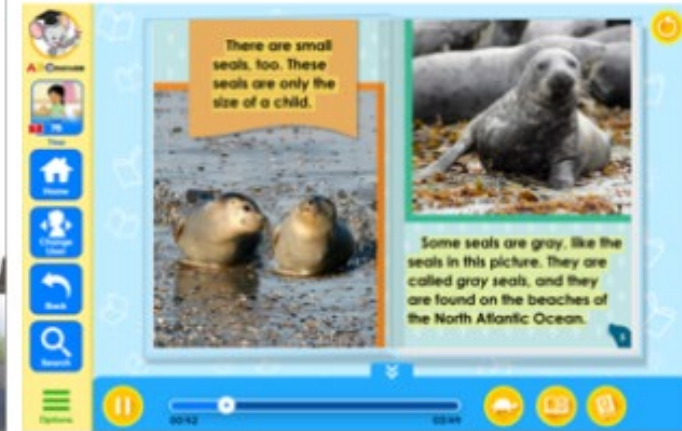
- Explored young children's perspectives on three reading modes: hard-copy books, an AI pronunciation feedback app, and an interactive narrated reading app



Reading Experience A:  
Hard copy book



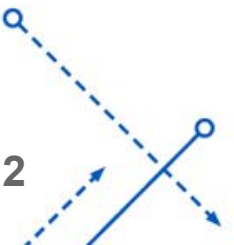
Reading Experience B: An app powered by an AI engine that responds to young children's read-aloud.



Reading Experience C: An app with massive book library which reads aloud for young children.

## Laddering interview 2: Young children's broader understanding of AI reading tools

- Children (5-8 years old) interacted with each reading mode and participated in laddering interviews about preferred features, reading experiences, and desired future app designs

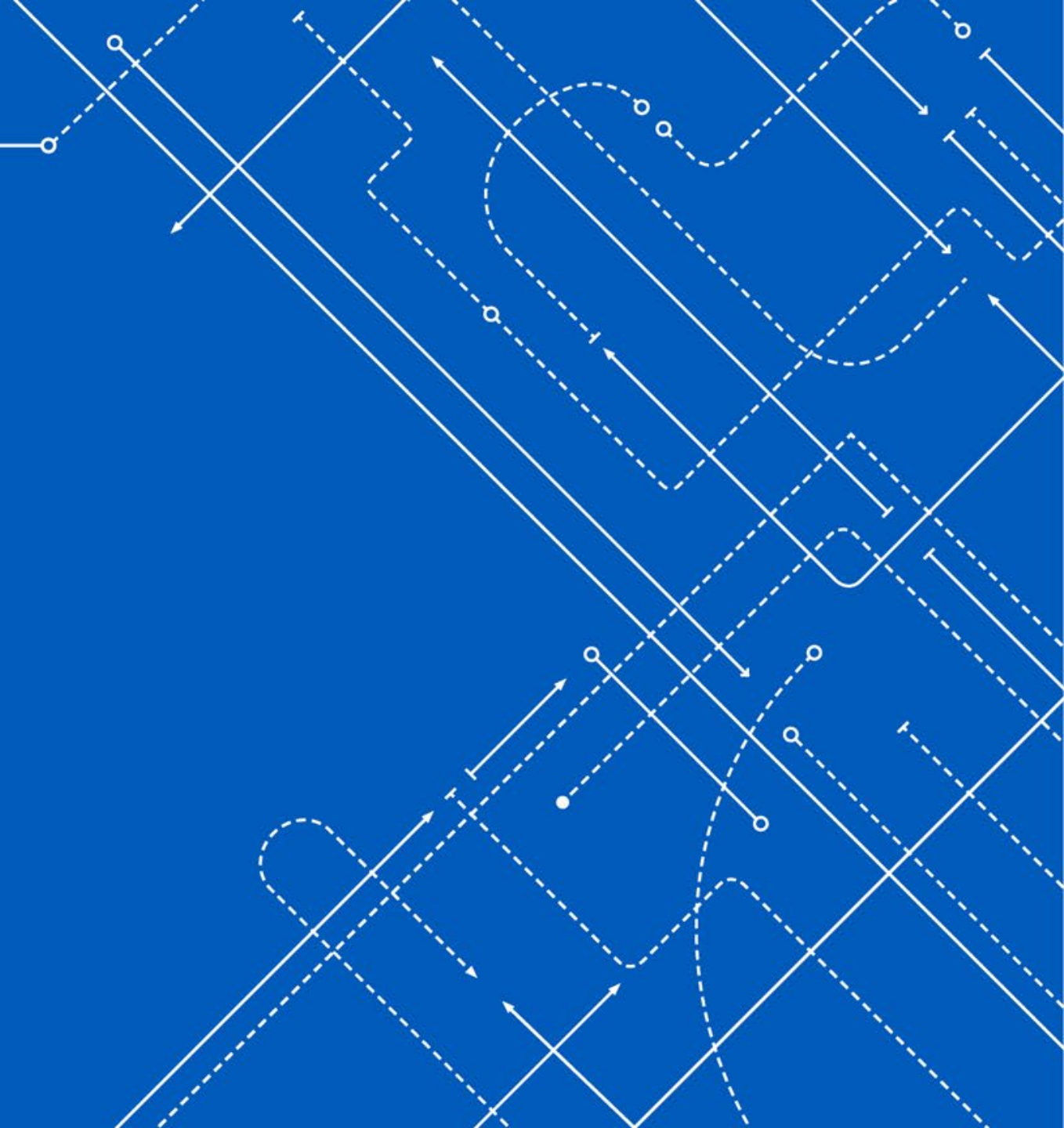


## Data analysis

- All interviews were video recorded, transcribed verbatim, and analyzed in ATLAS.ti 25
- Using the **Attribute–Consequence–Value (ACV) framework**, we first created quotations for each interview question and identified key attributes discussed by children
- Two researchers rewatched videos and reread transcripts to identify consequences and underlying values connected to each attribute

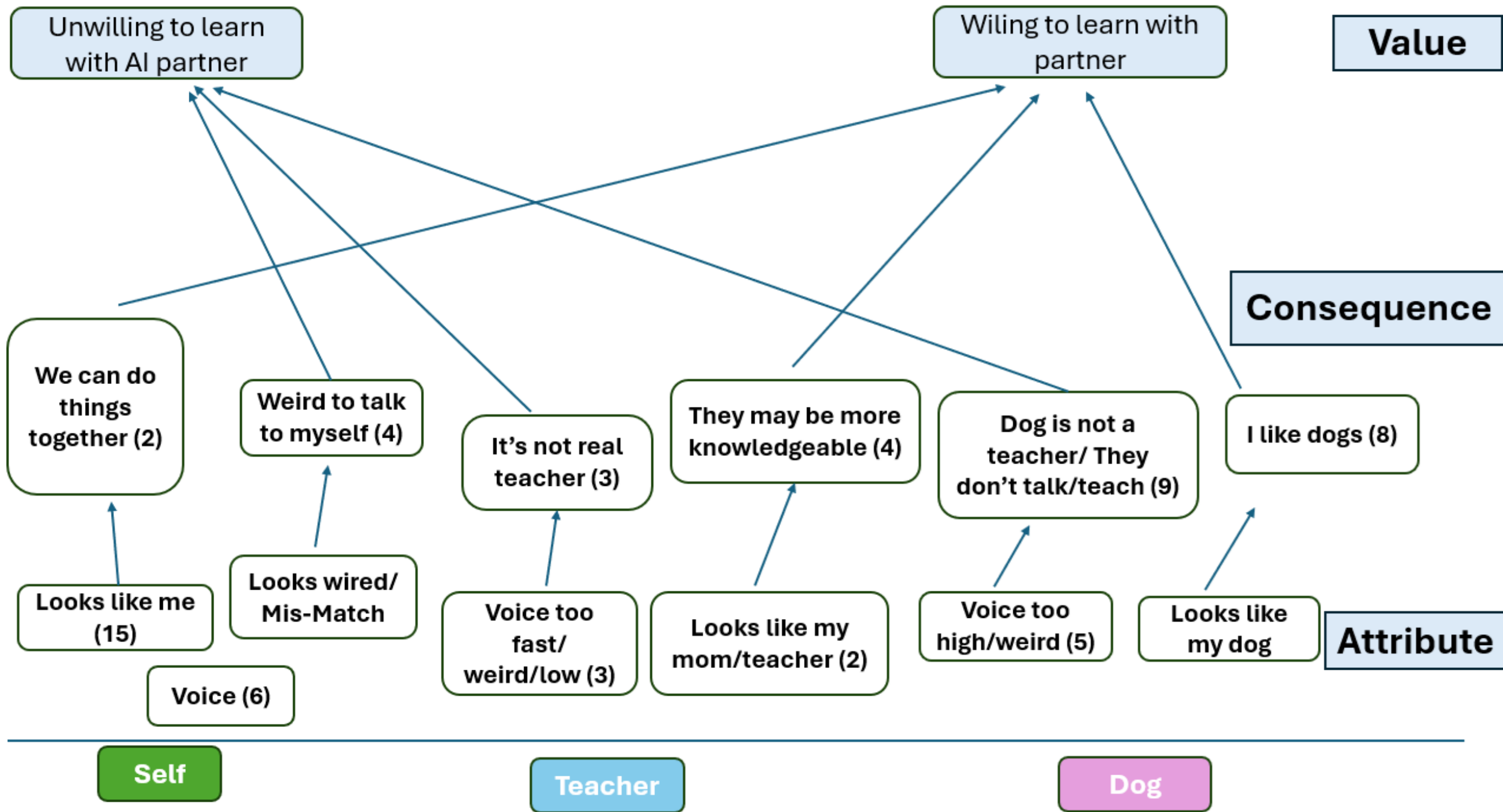


# FINDINGS



# Study1: Young children's perception towards learning with AI-generated avatars.

- Hierarchy Value Map (HVM)
  - illustrating how different *Attributes* of AI generated Avatars (Self, Teacher, Dog) led to perceived *Consequences*.
- **Willing to learn with an AI-generated Avatar:** Bonding to real-life experience
- **Unwilling to learn with AI-generated Avatar:**
  - Unfamiliar with character
  - Appearance mismatch
  - Previous negative experience toward the character in real life.



## Case 1.1: Willing to learn with AI generated avatar

### Attribute- Consequence Link

Interviewer: Can you tell me why you like this one (self-avatar) the most?

Corinne: Because it looks like me. **[A: Appearance Similarity]**

Interviewer: Where do you think it looks like you?

Corinne: It has my hair color. **[A: Appearance]**

Interviewer: Can you tell me how much you like to learn with your avatar, from one to five?

Corinne: This one. (Pointing to happy face emoji representing very happy)

Interviewer: You like to learn with yourself? Can you tell me why?

Corinne: Because we could like be friends and we can tell each other, like, interesting stories and we can make things up together. **[C: Social engagement & creative collaboration]**

## Case 1.2: Unable to connect AI generated Avatar to real life experience

### Attribute- Attribute Link

Interviewer: How much do you like to learn with the long-haired teacher, from one to five? (Showing Corinne five emotion faces)

Corinne: This one. Three. (Point the neutral face on the emoji paper)

Interviewer: Why three?

Corinne: Because it doesn't sound like a real person that much. **[A: Voice not real]**

Interviewer: How about the image?

Corinne: She kind of looks like a real person. **[A: Appearance]**

Interviewer: She kind of look like a real person, but just the sound doesn't sound like a real person?

Corinne: Yeah.

## Study 2: Balancing Assistance and Autonomy: Young Children's Value in AI-Enabled Reading A-C-V link

Interviewer: Which part do you like the most.

Dominic: The part that it could like, hear your voice, and then it transfers in words to like the AI, and then the AI corrects it. **[A: Automatic Speech Recognition (ASR)]**

Interviewer: So you like that AI to correct this like it was wrong. So how do you feel? Do you feel excited, or do you feel happy? Or do you feel like it felt challenging? Like, what, like, what is your experience if you use this app to read every day?

Dominic: like, probably a little harder than, like, reading from, like, the hard copy book. **[C: ASR lead to making reading more difficult]**

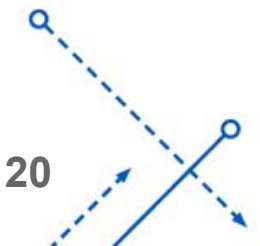
Interviewer: Why is it a little harder?

Dominic: Because, like, you're you have to, like, talk a lot, and it's harder than, like, actually reading it, because you're actually reading it and talking at the same time, so sometimes it doesn't come out, right?

**[V: Desire for balanced effort and accurate recognition]**

# Synthesizing Insights Across Cases: Uncovering Value Structures Through Laddering

- The two cases demonstrated multiple ladder structures within the ACV framework, including Attribute–Attribute (A–A), Attribute–Consequence (A–C), and full Attribute–Consequence–Value (ACV) connections
- Children were more likely to complete richer ladders when the AI feature or artifact aligned with familiar, meaningful, and recognizable experiences



## Conclusion

- Laddering interviews provided **a useful methodological approach** for uncovering how young children connect AI design features to personal meanings, especially during early-stage design before full prototypes
- Our findings suggest that even partial ladders can provide meaningful insight into how children make sense of emerging technologies and what they value in future learning environments.
- These laddering insights were perceived to be relevant to design by the research team and led to both design changes and new design conjectures

# Discussion and Implications

- Incomplete ladders revealed important developmental and contextual factors, suggesting that children's familiarity, comfort, and prior experiences shape how deeply they articulate consequences and values
- Future work may integrate laddering with co-design approaches to better capture how children reason, interact, and make meaning with emerging technologies in real time

# Acknowledgements

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# THANK YOU

Xintian Tu

[tuxintian@gmail.com](mailto:tuxintian@gmail.com)