DESIGNING FOR CHILDREN TO BUILD CONVERSATIONAL AGENTS AND LEARN ABOUT ARTIFICIAL INTELLIGENCE

By

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DESIGNING FOR CHILDREN TO BUILD CONVERSATIONAL AGENTS AND LEARN ABOUT ARTIFICIAL INTELLIGENCE

By

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As Artificial Intelligence (AI) becomes increasingly ubiquitous in society, conversational agents such as Siri, Alexa, and ChatGPT are shaping the experiences of younger generations. However, these young users often lack opportunities to learn about the inner workings of these AI technologies. One way to foster such learning is by empowering children to create AI that is personally and socially meaningful to them.

To address this educational need, my dissertation investigates research questions using a novel learning tool, AMBY ("AI Made By You"), which enables children to build their own conversational agents and learn about artificial intelligence without prior programming experience. AMBY was iteratively designed with and for children aged 12-13 through contextual inquiry and usability studies and has been deployed in an AI summer camp over two years.

In these summer camps, I explored learners' experiences and perceptions of using AMBY. Insights from these studies guided the development of AMBY 2.0, which introduced a new interface feature, "entity," to support abstraction and enhance the learning experience. Results from subsequent summer camps indicate that this feature aids in the better design of projects and mitigates learners' frustration.

Building on the summer camp deployment, my final dissertation study transitions to a formal learning environment: middle school science classrooms. In this classroom study, 100 children used the updated AMBY 2.0 interface in a between-subject experiment. The primary goal of this experiment was to evaluate the impact of the "entity" feature–an instance of data

abstraction–on students' enjoyment and project outcomes. Additionally, I investigated how the "Conversational AI + Science" learning experience shapes learners' attitudes toward AI and impacts their interest and knowledge.

This dissertation advances the field of human-computer interaction and computing education research by paving the way for the design and research of child-centered AI-authoring tools that enhance AI education for children. The findings highlight potential future directions for conversational AI learning environments, particularly in fostering attitudes and enhancing learning experiences in AI among middle school learners.

CHAPTER 1
INTRODUCTION

As artificial intelligence (AI) becomes increasingly ubiquitous in society, conversational agents such as Siri, Alexa, and ChatGPT are shaping the experiences of younger generations [16, 22, 17, 148]. Conversational AI applications include virtual agents [140], intelligent personal assistants [16, 118], and chatbots [127]. These applications are powered by complex AI algorithms and bring new opportunities to immerse children in AI-driven experiences. Such innovative use cases include increasing engagement in reading [145], supporting language learning [146, 43], promoting story comprehension and engagement [147], and fostering question-asking behaviors [8, 83].

Although opportunities for young people to *interact with* conversational AI are plentiful, opportunities to *deeply understand* how these technologies work are still scarce. Due to the complex nature of these AI technologies, many people, especially children, find it hard to see how these technologies work, these AI systems remain "black boxes". This lack of transparency can lead to many misunderstandings [31] and a noticeable gap between using AI and truly understanding it, which brings up important questions about whether future generations will be able to critically interact with and positively contribute to the development of AI. Fostering AI literacy can inspire more students to consider careers in AI, laying a strong foundation for their higher education and professional lives [74].

There have been efforts to establish frameworks for AI education at the K-12 level. Touretzky et al. [130] founded the AI4K12 initiative, which proposed five "big ideas" to navigate the landscape of AI education. These "big ideas" include perception, representation and reasoning, learning, natural interaction and societal impact [130]. For young learners, developing their own personally meaningful conversational agents can serve as a rich learning experience, shaping their perceptions and enhancing their understanding of AI [32, 135, 78]. However, there is a lack of developmentally appropriate tools for *learning to build conversational AI* [40].

Although platforms like Google Dialogflow [5], Rasa [3], IBM Watson [6, 35], and Azure Bot Service [2] offer robust development tools and a myriad of functionalities enabling skilled developers to construct advanced conversational AI applications, they often demand

extensive programming knowledge [111, 19]. Many of these features were not conceptualized to facilitate learning about AI in a manner that is authentic and effective for young learners, thereby presenting a barrier to fostering AI comprehension among this demographic.

My dissertation contributes to addressing this need by investigating its research questions in the context of a novel conversational AI development tool, AMBY ("AI Made By You"), designed for young learners to create their own conversational agents and learn about artificial intelligence without prior programming experience. Through a funded research project, Project DIALOGS[1], on which I played an active role in the design, development, and deployment of AMBY[2]. AMBY was iteratively designed over 14 months and has been implemented in AI summer camps for the past two years in Gainesville, Florida [62]. Within this period, AMBY has empowered 58 learners to build their own conversational agents. They expressed that AMBY provided them with the autonomy to develop personally meaningful projects [128]. The results from the summer camp demonstrate significant increases in learners' ability beliefs, willingness to share their learning experience, and intent to persist in AI learning [120].

In my dissertation, I have extended our work on summer camp implementation [62], conversational AI curriculum [120] and the development interface AMBY [68], to a formal learning environment, that of middle school science classrooms. The primary goal of the final experiment was to evaluate the impact of a novel interface feature to support abstraction–called *entity*–on students' outcomes. This feature is described in more detail later in this chapter. Additionally, I explored more broadly how conversational AI learning experiences shape learners' attitudes toward AI, as well as their interest and understanding of AI in the context of middle school science education.

1.1 Research motivation

My research targets middle school-aged children because this age has been identified as a key developmental period for interest and identity building [46]. A positive AI learning

1 Project DIALOGS: Fostering STEM Career Identity and Computer Science Learning through Youth-Led Conversational App Development Experiences (DRL-2048480) PI: Kristy Boyer, Co-PI: Maya Israel.

2 I would like to acknowledge the software developers who contributed to the AMBY codebase, including Amit Kumar, Sunny Dhama, John Tran Hoang, as well as the scholars who shaped its design and ideation, including Gloria Katuka, Yukyeong Song, Mehmet Celepkolu, Lydia Pezzullo, Joanne Barrett, Tom McKlin, Kristy Boyer, and Maya Israel.

experience during this age could significantly impact learners' interest and attitudes towards AI [74].

Letting children make conversational AI applications for learning is deeply rooted from Seymour Papert's Constructionism theory [98], which advocates for learning through hands-on creation. In particular, it emphasizes learner-centred education by encouraging learners to understand abstract concepts through designing personal and meaningful artifacts [58, 84, 26]. This approach is widely used in computing education and has led to many visual-based development environments (e.g., Scratch [108], App inventor [101]) to support young learners in designing and creating computational artifacts. Given the popularity of conversational AI applications in children's daily life, introducing AI through creating chatbots will foster children's learning about natural language processing, machine learning, and human-computer interaction. By designing what their chatbot can speak about and customizing chatbot's voice and personalities that resonate with their interests and experiences, children can promote a sense of ownership and investment in the learning process.

In this dissertation, I present AMBY as a "thick authentic" learning environment that deeply engages students in learning. Following Shaffer and Resnick's description for authenticity [119], AMBY provides a setting that students can create apps that are meaningful to them, incorporates real-world applications about AI, focuses on discipline-specific knowledge (AI and science), and supports assessment by using the chatbot artifact as a way for students to demonstrate their knowledge. This environment enhances the likelihood of meaningful engagement.

There is a growing recognition of the importance of introducing AI to all learners. The K-12 classroom emerges as an ideal setting for introducing AI. Children spend a significant portion of their lives in formal education environments, which presents a unique opportunity to integrate AI learning into existing curricula. Currently, many secondary-level AI learning tools and activities are implemented in informal learning environments such as summer camps and workshops [65]. Although informal learning offers flexibility and greater personalization, the absence of standardized curricula and teaching methods in such settings can lead to

inconsistent content and quality of education [94]. I aim to integrate AMBY, along with its conversational AI curriculum, in a formal learning environment because summer camps are opt-in experiences that serve only a subset of learners, whereas classroom experiences have the potential to include all learners in the partner teacher's classroom. I will investigate the appropriateness of the AI learning interventions within the context of middle school education, to ensure that our interventions are not only effective in informal learning settings but also relevant for formal learning settings to inform the evolution of curriculum being driven by the rapid AI advancements.

Transitioning the deployment of AMBY to in-school setting brings forth numerous benefits. Currently, there are limited classroom resources available within the schools to teach computing courses [23]. Few teachers have the necessary resources and expertise to introduce CS and AI concepts to their students [93]. Bringing AMBY and the conversational AI curriculum into the classrooms can bridge this gap by providing an accessible platform for learning AI concepts in a relevant and engaging manner. Given AI's interdisciplinary nature, embedding AMBY within subject-specific curricula, such as science and language could enhance students' understanding and engagement without straining already limited educational resources.

I chose the science classroom as the starting point of the transition, as middle school science standards in the state of Florida–and similarly in other states–contain essential AI components as learning objectives. These standards requires students to understand the concept of AI and recognize the responsible use and ethical implications of AI technologies[3]. While there have been efforts to develop AI curriculum at the middle school level [138, 141], a gap still exits in understanding how to integrate AI learning environments and curricula in to the core subjects such as science.

Through my multi-year user studies of AMBY, we have continuously updated AMBY with new features, which the two major versions I name as AMBY 1.0 and AMBY 2.0. Both AMBY 1.0 and 2.0 support users in generating training data and visualizing conversation flow. They also allow both written and spoken input and output modalities and enables users to

3 Florida K-12 standards (relevant middle school CS and AI objectives are SC.68.CS): https://www.cpalms.org/public/search/Standard.

customize the voice and appearance of their agents. Users can deploy their new conversational agents from AMBY to a website, they can even access their agents by calling them on the phone. We deployed AMBY 1.0 in summer 2022. The results from the previous camp inspired us to design and develop a new set of features for AMBY to support more diverse use cases. In summer 2023, we introduced AMBY 2.0, with the new feature called *entity*. The *entity* feature allows users to create more personalized responses for their agents and become more efficient in creating training phrases, thus enhancing the overall user experience.

Abstraction is a fundamental concept in computing and its importance has been widely recognized [87, 12]. Abstraction usually involves simplifying complex systems by focusing on the main ideas and hiding irrelevant details [142]. In AMBY, some training phrases share similar attributes, which can be bundled to a single *entity* and reused across different intents. The entity feature allows students to simplify the tasks of writing repetitive training phrases and focus more on other important aspects of project development. Similar to the concept of *variables* in programming, which Grover et al. [47] describe as a form of data abstraction, the *entity* feature in AMBY 2.0 serves as a data abstraction tool when designing conversational agents.

Teaching abstraction has become an important learning goal in both K-12 and higher education [14, 1, 95]. However, research indicates that abstraction is not sufficiently emphasized in the classrooms by the teachers [91] and effectively utilized by the students [12]. For example, studies have highlighted CS undergraduates' struggles with algorithms [103, 12] and students' reluctance to utilize abstract classes in object-oriented programming [95].

Abstraction can be especially challenging when dealing with children. Piaget's theory of children's cognitive development initially suggested that children develop the ability to abstract at the formal operational stage, around age 11-12 [104]. However, later they updated that children begin using abstraction from as young as 18 months [20]. This aligns with research in computing education, which suggest that teaching abstraction skills should start early and be revisited throughout educational levels [77, 87].

To tackle challenges in teaching abstraction, *entities* can be an effective tool to enhance children's abstraction skills in the context of AI education. Researchers have proposed various

strategies to specific contexts such as formal modeling [29], algorithm design [12] and game development [47]. With the growing influence of AI, there is now a significant opportunity to further enhance children's abstraction skills in the context of AI. For instance, image classification tasks require learners to identify and abstract the key features that characterize each class of images. Similarly, *named entity recognition*, a prevalent task in natural language processing, involves categorizing textual entities into predefined groups such as locations, names, and quantities.

AMBY introduces a simplified version of *named entity recognition* that allows students to define the categories of entity and incorporate them into their project. This aims to enhance their abstraction skills with AI applications.

1.2 Research Questions and Hypotheses

1.2.1 Research questions

The overarching research question guiding my dissertation is: *How can we provide engaging and authentic AI learning experiences for children?* To investigate this research question, my design goal is to empowers children with AI learning through creating their personally relevant conversational AI projects. Through an iterative design process with both adults and children, our team have designed a learning environment, AMBY, to support children in creating conversational agents (Chapter 3). As part of a collaborative team, I first deployed AMBY to a summer camp. After the camp, I explored the following research questions (RQs):

RQ1 How do children engage with a development environment designed to support them in making conversational agents?

RQ2 What features do children desire in a learning environment to support their educational needs?

To answer these RQs, I explored the experiences and perceptions of middle school-aged children interacting with AMBY during a summer camp (this work is detailed in in Chapter 4). The study revealed that while learners were engaged and creative, they also encountered challenges, particularly with the labor-intensive data entry required for effective AI

performance and a desire for more personalized chatbot responses. These insights informed the development of AMBY 2.0, which integrates the *entity* functionality feature (Chapter 5). Through our summer camp study in 2023, I observed learners' interactions with this new feature, which suggested the necessity of a more rigorous experimental study to evaluate its impact on AI learning experiences. In my final study (Chapter 6), I investigated RQ3 through a middle school classroom study with 100 participants using AMBY 2.0.

RQ3 Does *entity* feature impact students' enjoyment and artifact quality?

In my final study, I first describe an updated, science-oriented conversational AI curriculum, which has been developed in partnership with three middle school teachers, containing examples related to previously learned science topics, and activities that are closely tied to students' previous science learning experiences. During the classroom study, students learned conversational AI concepts, and worked with a student partner to develop a conversational agent with relevant science topics using AMBY. The classroom activities spanned 10 class sessions of approximately one hour each.

During the classroom study, one of my goals was to assess the effectiveness of the new entity feature in AMBY 2.0 (RQ3). Previous results from summer 2023 (Chapter 5) have indicated that this feature, which is a form of data abstraction, can aid in better design of agents and mitigate learners' frustration due to the repetitive entry of training data.

1.2.2 Hypotheses

Hypothesis 1: The entity feature will **enhance students' enjoyment** in creating chatbots, as indicated by the post-questionnaire. This hypothesis is supported by the literature, which suggests that abstraction enables students to concentrate on higher-level concepts rather than on unnecessary low-level details [87]. Employing more intuitive data representations can make programming more engaging. Moreover, the introduction of the entity feature encourages learners to integrate this unique element into their project designs to build more creative artifacts. This enhancement could lead to increased enjoyment, engagement, and a sense of ownership over their projects.

Hypothesis 2: The chatbot artifacts produced by students in the entity condition will exhibit **higher project quality,** using a validated rubric (Cohen's Kappa = 0.751) to evaluate

across four aspects: project ideation, conversation design, AI development, and end-user satisfaction. More details about these aspects can be found in Chapter 6. This hypothesis stems from the capability of the entity feature to allow students to personalize responses based on end-user input, thereby enhancing the conversational design and AI development. Such personalized responses are likely to be perceived as more relevant and satisfactory by end-users, which improves the overall project quality.

Experimental Conditions. My goal is to investigate the impact of the *entity* feature on students' enjoyment and the project quality. To this end, I conducted a between-subject experiment using two versions of AMBY: *AMBY with entity* and *AMBY without entity*. Each of the six class sections was assigned to one of the conditions, where all participants in each section created their science chatbots using AMBY in the condition they were assigned to.

1.2.3 Post-hoc Analysis of Classroom Outcomes

In addition to addressing RQ3, I conducted a post-hoc analysis on the outcomes of the "conversational AI + Science" classroom intervention. This analysis included reporting on AI attitude changes, interest in conversational AI, and students' knowledge about AI. The attitude change was measured by assessing ability beliefs, identity and persistence in AI learning from pre- to post-questionnaire [120]. The interest outcomes consist of triggered situational interest and maintained situational interest in conversational AI [4] measured in the post-questionnaire. Based on Hidi and Renninger [51]'s interest development model, the development of interest contains four phases: 1) triggered situational interest; 2) maintained situational interest; 3) emerging individual interest; and 4) well-developed individual interest. Our classroom intervention specifically addresses phases 1 and 2 and hopes to trigger and then maintain students' interest in conversational AI as they find developing conversational agents to be meaningful. Student learning was assessed through a paper-based test on the conversational AI concepts taught in the class. As students in both experimental conditions completed the conversational AI development task, I do not expect any significant difference in students' AI learning between the entity and non-entity condition. More details about these outcome measurements can be found in Chapter 6.

4 The interest formation instruments were collaboratively developed within the Project DIALOGS team, led by the project external evaluator, Tom McKlin.

1.3 Dissertation Document Overview

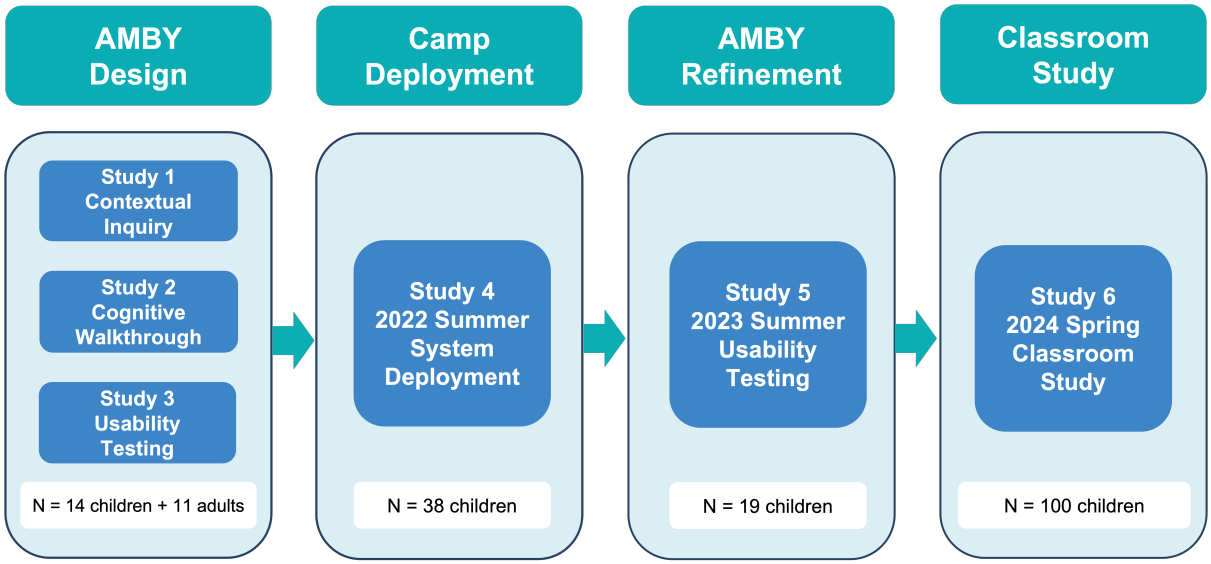


Figure 1-1. Dissertation study overview.

Figure 1-1 provides a overview of my dissertation studies, which contains four distinct phases related to the iterative design and deployment of the learning environment that fosters AI learning: AMBY Design, Camp Deployment, AMBY refinement and the final classroom study. The structure of this dissertation is as follows:

Related Work (Chapter 2): I conducted a literature review on digital learning environments that support the teaching of conversational AI and, more broadly, natural language processing in K-12 settings. This chapter also reviews existing conversational AI development tools tailored for both adults and children and offers an overview of fundamental conversational AI concepts and terminology.

AMBY 1.0 Design (Chapter 3)[¶]: Over the course of a year, we engaged in a series of iterative design studies with middle school students and adults to conceptualize and create AMBY from scratch.

AMBY 1.0 Camp Deployment (Chapter 4): This chapter shares insights from the AMBY camp deployment study conducted in the summer of 2022. During this time, 39 middle school learners used AMBY to create 58 conversational AI projects. I explore the experiences and perceptions of middle school-aged children interacting with AMBY.

¶ Work detailed in Chapters 3 and 4, titled "AMBY: A Development Environment for Youth to Create Conversational Agents," has been accepted to the International Journal of Child-Computer Interaction, with me as the first author.

AMBY 2.0 Design and Refinement (Chapter 5): Stretching from Fall 2022 to Summer 2023, this phase focused on refining the AMBY environment, culminating in AMBY 2.0. Driven by insights from AMBY 1.0 user studies, we incorporated new features, including the *entity* feature, to enhance students' learning experiences. This chapter reports the results from our user study on AMBY 2.0 in Summer 2023.

AMBY 2.0 Classroom Study (Chapter 6): The final stage is the deployment of AMBY 2.0 in a middle school science classroom in Spring 2024. This chapter reports the findings of the impact of the *entity* feature on students' enjoyment and project outcomes as well as post-hoc findings about the classroom intervention.

CHAPTER 2
RELATED WORK

This work stands at the intersection of AI in K-12 education and conversational AI development. This chapter first presents a literature review of digital learning environments for teaching AI (specifically Natural Language Processing) to youth. This is followed by an examination of existing conversational AI development tools for both youth and adults. Lastly, I introduce the fundamental conversational AI concepts and terminology.

2.1 A Scoping Review of Digital Learning Environments for Teaching Natural Language Processing in K-12 Education

Conversational AI, also known as dialogue systems, is a subset of Natural Language Processing (NLP). NLP is a crucial element in AI education due to its role in facilitating machine understanding, interpretation and generation of human language [131, 52]. The AI4K12 big ideas highlight many NLP tasks and applications for children to grasp. As per Touretzky et al. [130], students should understand basic NLP concepts such as speech recognition (big idea #1), word embeddings (big idea #2), parsing (big idea #3), text generation and sentiment analysis (big idea #4), as well as ethical concerns related to NLP applications (big idea #5). To foster students' growth from AI consumers into AI creators, learning environments must provide authentic, hands-on learning experiences [119, 81]. Such experiences can be facilitated through relatable NLP tasks that simulate real-world applications, such as creating personalized chatbots and exploring sentiment analysis models.

The objective of this study is to investigate the state of the art in digital learning environments for learning NLP in the context of K-12. I aim to characterize and compare the implementation and evaluation of these tools to identify gaps and potential opportunities for future conversational AI research.

2.1.1 Literature Search

The methodology for this scoping review is based on the framework outlined by Arksey and O'Malley [11] to search and review existing literature. Based on the research questions, I identified two main term-categories to include in the literature search: discipline (NLP-related) and target population (K-12). After performing multiple iterations of searches, I derived a list of relevant synonyms for each category. The search terms were applied over both

the titles as well as the abstracts of the publications. In the literature search, we used the combined keywords from the two categories (Table 2-1). The complete search string was ("AI Learning" AND "AI Education" AND "AI literacy" AND "NLP" AND "natural language processing" AND "linguistics" AND "conversational AI" AND "dialog* system" AND "chatbot") OR ("K12" AND "middle school" AND "high school" AND "elementary" AND "primary school" AND "secondary education" AND "youth" AND "kid" AND "child*"). The actual string varied based on the restrictions of each database.

Table 2-1. Keyword list for literature search

Category (connected using "and" logic)	**Search terms (connected using "or" logic)**
Discipline	AI Learning, AI Education, AI literacy, NLP/natural language processing, linguistics, conversational AI, dialog(ue) system, chatbot
Target population	K12, middle school, high school, elementary/primary school, secondary education, youth, kid, child*

2.1.1.1 Sources

We searched the main digital databases and libraries in the field of computing, including ACM Digital Library, IEEE Xplore, ScienceDirect and Google Scholar. In addition, we also used Google search to account for the possibility that some educational tools may not yet have been published in scientific databases [105]. Since research on the topic of NLP education is fairly new, recent works are most often published in niche conferences and workshops, including AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI), Special Interest Group on Computer Science Education Technical Symposium (SIGCSE), Interaction Design and Children (IDC), ACM CHI Conference on Human Factors in Computing Systems (CHI), Computer-Supported Cooperative Work (CSCW), IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC). We performed additional searches in these proceedings to minimize the risk of omitting relevant works.

2.1.1.2 Selection criteria

Based on the goal of this literature review, following the criteria described in Tatar and Eseryel [124], the selection criteria for this literature review are shown in Table 2-2.

The initial literature search was conducted in March 2022. A second search was

Table 2-2. Selection criteria for NLP learning tools for K-12

Inclusion criteria	**Exclusion criteria**
K12 education (kindergarten through the 12th grade)	Other stages of education such as pre-university level, college, and graduate level
Empirical studies	Theoretical studies
Involves tools or technologies	Studies that do not involve digital tools (e.g., curriculum design, unplugged activities only, workshop design)
Report at least one form of assessment (e.g., learning outcomes, engagement, perception)*	Studies that do not provide assessment*
English publications	Non-English publications

Note. Criteria marked with an asterisk (*) were used for selection of papers answering the research question "How have researchers evaluated these tools in educational contexts?" only.

conducted in February 2023 to include any additional papers published between March 2022 and February 2023. The searched papers were screened by scrutinizing their titles and abstracts to determine their eligibility based on the selection criteria. Because this field is still new, some learning environments are still works-in-progress and thus lack a published system evaluation. However, it is still important to include these tools for the completeness of this review. Through backwards and forwards snowball sampling, this review ultimately yielded 21 publications describing 11 learning environments.

2.1.2 What digital learning environments are available for NLP learning in K-12 education?

I identified 11 digital learning environments developed for NLP learning in K-12 education. These learning environments and corresponding evaluation studies are found in 21 publications (some systems involve multiple studies published as different papers). Below I will briefly introduce four learning tools that specifically aims to teach conversational AI concepts[1].

1. **Convo [150, 149]:** Two graduate students at MIT developed Convo for middle school students. As a conversational programming agent, Convo enables students to create deep learning-based conversational AI agents. It provides a learning environment that explores AI-driven communication systems and their applications.

2. **Zhorai [78]:** Created by researchers at both Harvard Graduate School of Design and

1 A complete set of learning environments for teaching NLP is available as in the preprint https://arxiv.org/abs/2310.01603

MIT, Zhorai is a conversational agent that teaches AI/ML concepts through interactive dialogue for young users (aged 8-11). It focuses on representation and reasoning, learning, and the social impact of AI.

3. **ConvoBlocks [134, 133, 135, 136]:** ConvoBlocks is a block-based programming interface developed by MIT for learners between the ages of 11-18. It offers a hands-on experience in training, transfer learning, large language models, intents, societal impact and ethics, speech synthesis, and speech recognition.

4. **Build-a-Bot [102]:** Developed by researchers at MIT, Build-a-Bot is an open-source tool designed for classroom environments. It introduces students to the NLP pipeline, which includes data collection and labeling, data augmentation, keyword filtering, intent recognition, and question answering, serving as a valuable resource for teaching AI concepts.

Most of these tools are available as web applications, which makes them easily accessible to anyone with an internet connection. Of the above tools that are publicly available, most are available for free, but some are restricted to registered users (e.g., NLP4All, eCraft2Learn) or require an API key to access them (e.g., Cognimates). 7 out of 11 tools allow users to deploy the artifact (a working application or a trained model) to an external site. Three tools do not offer external integration and one tool does not mention integration. Regarding language support, six tools only support English, while five support at least one more language in addition to English. Among those five tools that support more than one language, three tools offer multiple (10+) choices.

2.1.3 Key Findings, Research Gaps and Implications

Next, I summarize the key findings from this scoping literature review. In total, I identified 11 digital learning environments for NLP learning in K-12 education, with most being accessible as online web apps. However, some tools have limitations such as restricted access or language support, which may affect their usability for beginners.

The 11 digital learning environments for NLP in K-12 education primarily support text classification, speech recognition, and intent recognition tasks, with limited support for other

popular NLP tasks. These tools offer varying capabilities for training and deploying NLP models and provide different data input modalities, such as keyboard and speech. However, the majority of the systems lack in-depth scaffolding and explanations for NLP processes, which could be improved for better learner understanding.

A majority of the studies employed mixed methods for evaluating their tools, with moderate sample sizes ranging from 3 to 135 (median = 29.5). Research studies were more often deployed in informal learning contexts than formal contexts.

Most NLP learning activities target middle and high school students, with evaluations focusing on AI knowledge assessment and learning experiences. These tools prove effective for teaching NLP and AI concepts, fostering interest, and improving students' understanding and engagement. However, learning challenges persist in machine learning and ethics concepts, and there is more work to be done in addressing issues of over-trusting technology.

The analysis of my literature review revealed six prominent gaps. First, there is a limited variety of NLP tasks, with a strong focus on natural language understanding (NLU) and limited exposure to other essential NLP tasks. Second, comprehensive evaluation methods for NLP learning tools, particularly for younger students, are still underdeveloped. Third, while many pedagogical systems provide explanations, they often fall short in offering intuitive insights and comprehensive understandings of NLP concepts. Fourth, there is a limited focus on younger children, with most tools targeting middle and high school students. Fifth, there is insufficient personalized learning experiences tailored to diverse learners' unique needs. Lastly, the literature lacks concrete recommendations for effective teaching strategies to incorporate NLP education efficiently in K-12 settings.

My dissertation directly addresses these gaps by developing and deploying a novel educational tool, AMBY, which broadens the variety of NLP tasks accessible to novice students through an engaging and intuitive interface. I have also developed a validated rubric to assess the AI artifact created on AMBY, which enhances the evaluation of NLP learning experiences for young learners. The system provides rich and interactive explanations that fosters deeper understanding of AI. Through the deployment of AMBY in middle school science classrooms, my research offers concrete, empirically-supported instructional resources

for integrating conversational AI into K-12 education.

2.2 Conversational Agents and their Role in Learning

Conversational agents, or chatbots, communicate with users in natural language (text, speech, or both) [57]. With rapid advancements in the fields of AI and machine learning, modern conversational AI systems are robust enough to serve users in everyday life. A growing body of research is exploring how these systems can play a role in learning.

Druga et al. [33] specifically investigated young children's perceptions of, and interactions with, conversational agents, and proposed a series of design considerations to engage young children in the interaction. For instance, voice and prosody features were found to be decisive in children's perceptions of friendliness with agents. Hoffman et al. [54] found that children, as reported by their parents, tend to establish meaningful emotional connections with conversational agents, perceiving them as entities capable of feeling and eliciting emotions. Garg and Sengupta [39] explored children's and parents' perceptions of using conversational technologies for in-home learning, finding that children had high expectations for these devices' knowledge and capabilities for naturalistic interaction, and that parents found these technologies' potential role in learning to be desirable, while also wanting to monitor their children's usage.

Lovato and Piper [82] reviewed studies of children's voice-search technology use from developmental and human-computer interaction perspectives, and concluded that since children's question-asking serves a developmentally different and important role than the question-asking of adults, conversational interfaces should be able to identify child users and be prepared to respond to their questions in different, appropriate ways. In this spirit, Oranç and Ruggeri [96] explored how young children of different ages ask questions to conversational agents, finding that while all children could identify when answers were irrelevant, only older children, who were more familiar with conversational agents, tended to adapt their question-asking when an agent's answers were unhelpful. Similarly, Girouard-Hallam and Danovitch [42] investigated how young learners use conversational agents as information sources, and found that children's trust in conversational agents as information sources increased with age.

Some researchers have applied insights such as those described above to implement and evaluate novel interactive learning experiences using conversational AI. For example, Xu and Warschauer [144] embedded conversational agents into animated television programs to help children (ages 4-6) improve science learning by asking questions, providing feedback and offering scaffolding. Lovato et al. [83] engaged young children in creative storytelling with embodied stuffed animal agents to explore playful conversational agent design. These burgeoning efforts demonstrate the potential for conversational AI to support youth learning experiences.

A recurring theme in designing educational technologies for younger audiences is the importance of authenticity and meaningful engagement [119, 117]. Designing for younger demographics often involves direct collaboration with the intended age group, taking into account their needs and desires [25, 27]. In alignment with these prior work, my work with AMBY involved iterative design processes with middle school youth to ensure that the tool aligns with learners' interests and preferences while also addressing their social and educational needs.

2.3 Conversational AI Development Tools

There have been numerous efforts to foster learning *about* conversational AI. Many popular AI education platforms for youth have integrated specific modules that involve some aspects of conversational AI, such as Cognimates [31], LearningML [38, 110], ML4K (Machine Learning for Kids) [69], Zhorai [78] and eCraft2Learn [60]. However, most of these systems only allow users to engage with a subset of conversational AI concepts (*e.g.*, natural language processing) rather than allowing users to engage in building conversational AI applications themselves.

Currently, there are several robust tools developers have access to for creating conversational applications. These tools (e.g., Google Dialogflow [5], Rasa [3], IBM Watson [6, 35], Amazon Lex [89], Azure Bot Service [2], and Wit.ai [4]) offer a plethora of functionalities for skilled developers to create advanced conversational AI applications. However, these tools are not well suited for educational purposes that target young learners. Many features require extensive programming knowledge [111, 19] and were not designed for

fostering AI learning in a robust and authentic manner for young learners.

There have been efforts to close this gap, designing systems specifically for young learners to learn about conversational AI by building it. For instance, Van Brummelen [133] introduced conversational AI modules within MIT App Inventor, enabling students to program Alexa Skills in a block-based programming environment. In a five-day workshop involving 47 students aged between 11 to 18, the researchers observed significant learning gains in general AI and conversational AI concepts. Zhu and Van Brummelen [150, 149], on the other hand, developed Convo, a conversational programming agent that enables students to create deep learning-based conversational agents. Through Convo's user study, the authors observed an increase in the participants' confidence in their abilities to build conversational agents.

Despite these advances, these tools still present limitations, particularly in supporting the design of sophisticated, multi-turn conversations, a cornerstone of conversational logic. Our novel interface, AMBY, aims to address this by incorporating dialogue concepts into the design process. Incorporating dialogue concepts into AI learning environments is critical as it gives learners a tangible understanding of conversational AI. This understanding aligns with the principle of natural interaction, one of the "Five Big Ideas for AI Education in K-12" outlined by Touretzky et al. [130]. This principle emphasizes the need for learners to understand how AI systems mimic human communication in an interactive and dynamic manner. Through engaging with these concepts, learners may develop a more nuanced understanding of how AI systems manage complex, multi-turn dialogues. Moreover, this approach may encourage critical thinking and foster communication skills as learners navigate diverse conversational scenarios, ensuring their AI responds appropriately. Additionally, AMBY offers the option to customize the agent's appearance and voice, a feature designed to enhance engagement and learning. Previous studies have indicated the significance of this capability [56, 50]. Another key distinction is that youth were actively involved in AMBY's design process. Unlike previous systems, our method ensured that the users themselves were involved in the iterative design process, allowing us to tailor the tool more effectively to meet learners' needs.

2.4 Conversational AI Development Concepts and Terminology

This section provides an overview of conversational AI development concepts involved in the task of developing conversational agents. A simple conversational AI system consists of several modules. It takes the user's speech and processes it in the *speech understanding module*, which converts the speech signals to text and infers the user's ***intent*** by matching the text with a pre-defined category[2]. For example, when a user says, "Can you suggest a movie to watch?", the *speech understanding module* processes the user input and identifies the user intent as "Request movie recommendation". After recognizing the user's intent, the *speech understanding module* sends this information to the *dialogue manager* to decide what action to take based on the user's intent and select from a list of ***responses*** to return to the user. For example, the "Request movie recommendation" intent might serve responses such as "You might like to watch *Owls of Magic*" or "My suggestion is *Wizards and Armies*". Once the response is selected, the system sends it to the *speech generation module*, which transforms this response into speech output and returns it to the user.

A conversational AI's intent recognition accuracy is largely constrained by the robustness of its training data (also called ***training phrases***). These phrases induce the model to capture different linguistic manifestations of the same intent. As a developer, authoring intents, associated training phrases, and responses are core activities to creating a conversational AI. Additional activities include authoring ***follow-up dialogues*** and creating ***fallback intents*** which are used when no other intent is recognized in the user's utterance.

2 Some conversational systems are textual and omit the speech recognition step as well as the speech generation module mentioned below.

CHAPTER 3
PHASE 1: AMBY 1.0 DESIGN

This chapter[1] describes my work which aimed to design a learning environment that empowers children with AI learning through creating their personally relevant conversational AI projects.

To develop AMBY, we[2] utilized an iterative design approach, working with youth at multiple design stages (Figure 3-1). This process consisted of three studies in total. Study 1, conducted in 2021, was a contextual inquiry (Section 3.1) during a summer camp with 14 youth. The feedback derived from this contextual inquiry and the literature-driven design principles (Section 3.2) informed the initial AMBY prototypes. We conducted two usability studies to pilot the system and identify potential issues. The first usability study, Study 2 (Section 3.3), was a cognitive walkthrough with expert reviewers. The second usability study, Study 3 (Section 3.4), was a think-aloud usability test with youth who had also participated in the contextual inquiry the year prior (Study 1). The AMBY 1.0 features and technical implementation is described in Section 3.5.

3.1 Study 1: Contextual Inquiry

Contextual inquiry is a widely used technique that consists of observing and talking with people in the context of performing specific tasks [107], which can inform the design of a system that will support an improved work experience for the target users [137, 71]. In this contextual inquiry study, our goal was (1) to investigate how youth learners use an existing conversational agent development tool, Dialogflow[3], to create their own conversational agent in a summer camp and (2) to identify their challenges and needs to accomplish their development goals. We chose Dialogflow for the following reasons: 1) it is free and publicly available; 2) it provides detailed documentation and guidance for small and simple

1 Work described in Chapter 3 and 4 has been published as a journal article. Reference: Tian, X, Kumar, A., Solomon, C. E., Calder, K. D., Katuka, G. A., Song, Y., Celepkolu, M., Pezzullo, L., Barrett, J., Boyer, K. E., & Israel, M. (2023). AMBY: A Development Environment for Youth to Create Conversational Agents. *International Journal of Child-Computer Interaction*, 38, 100618.

2 This work represents a collaborative endeavor involving all named authors listed above. As the first author, I took the lead in designing the AMBY interface prototypes, outlining the user interaction flow, and specifying the feature functionality. I also developed the research instruments used in the usability studies with adults and children (study 2 and 3) and was responsible for overseeing the data collection (study 2 and 3) and analysis (study 1, 2 and 3). The majority of initial manuscript draft was written by me.

3 https://dialogflow.cloud.google.com/

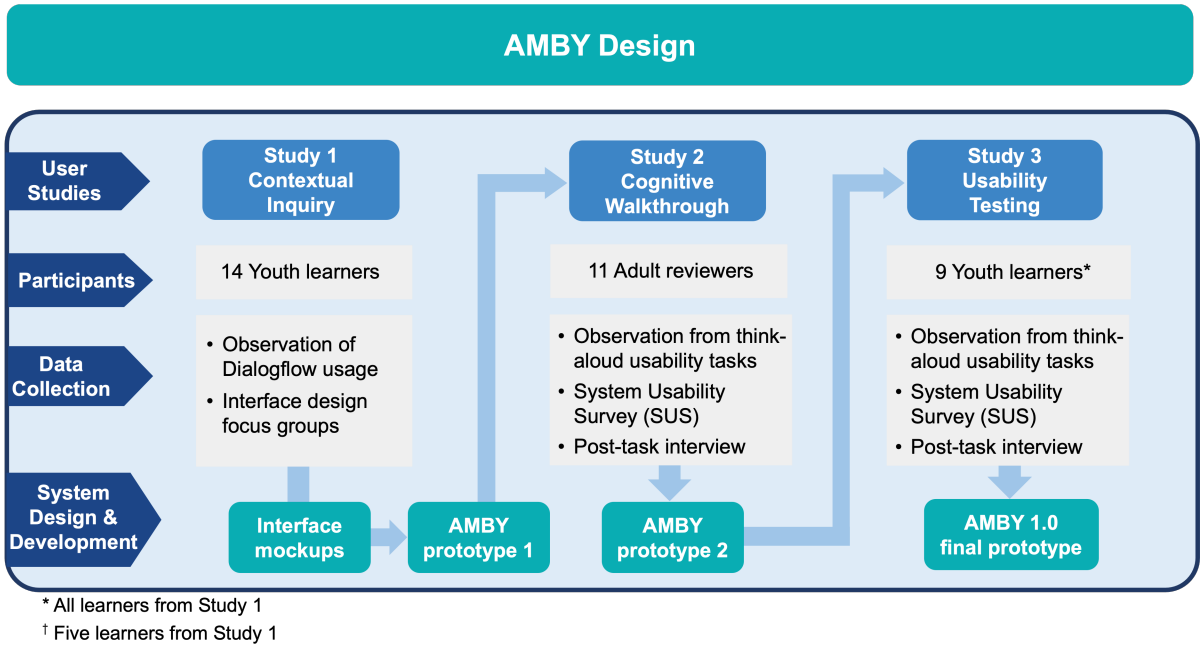


Figure 3-1. Overview of phase 1: AMBY design studies.

agent-development tasks; 3) it utilizes state-of-the-art language training models; and 4) it offers easy integration to other platforms, such as Google Assistant and Google Home devices.

3.1.1 Participants

In the summer of 2021, 14 youths attended the summer camp. Our participants came from a primarily Black community in the southeastern United States. We held the summer camp at no cost to their families at a local community center. Among the 14 participants, 2 identified as female and 12 as male; 11 as Black/African American, and 3 as White/Caucasian. The average age of the participants was 12.3 (SD = 1). Seven participants (50%) reported having no prior coding experience; the remaining seven (50%) reported having block-based coding experience (e.g., Scratch).

3.1.2 Camp Context with Dialogflow

During the two-week summer camp, students learned about foundational principles of artificial intelligence and conversational AI (Figure 3-2). In the first week of the camp, the participants learned about important AI concepts as they applied to Dialogflow, such as machine learning, conversational AI, intents, training phrases, responses, parameters, contexts and follow-up intents (these terms were defined in Section 2.4). In the second week, learners worked in pairs to build a conversational agent using Dialogflow, with a topic or purpose of

Figure 3-2. Left: Summer camp 2021 classroom. Right: Interface design focus group. Learners are presented with paper mockups, guided by a camp facilitator.

their choice. They integrated and tested their conversational agents with Google Assistant, as well as on a Google Home Mini device. The camp also provided CS/AI Unplugged activities [79] and social activities. Eight camp facilitators recruited from the researchers' university worked closely with learners on their project development and also reported daily observations, noting the challenges learners faced while using the Dialogflow interface. Facilitators observed the learners' behavior throughout each day, and documented any issues they noticed in a daily reflection entry. In the reflection entry, the facilitators responded to prompts such as "what went well today," "what can be improved, and how," along with any questions or concerns they had. Facilitators would have been familiar with some of the challenges that learners might be facing as Dialogflow novices, as none of the facilitators had had any Dialogflow experience prior to their own training in the weeks prior to camp. These facilitator reflection entries were carefully noted and examined together by two researchers to extract themes.

3.1.3 Dialogflow Challenges

This section presents our observations from the contextual inquiry with learners using Dialogflow during a summer camp.

- **Limited affordances for conversational AI design**: While Dialogflow can support sophisticated conversational app development, its interface does not support novices in applying conversational AI design concepts (Section 2.3). Learners rarely used the advanced features that were discussed in lessons and mostly used the basic elements of each intent (i.e., training phrases and responses).

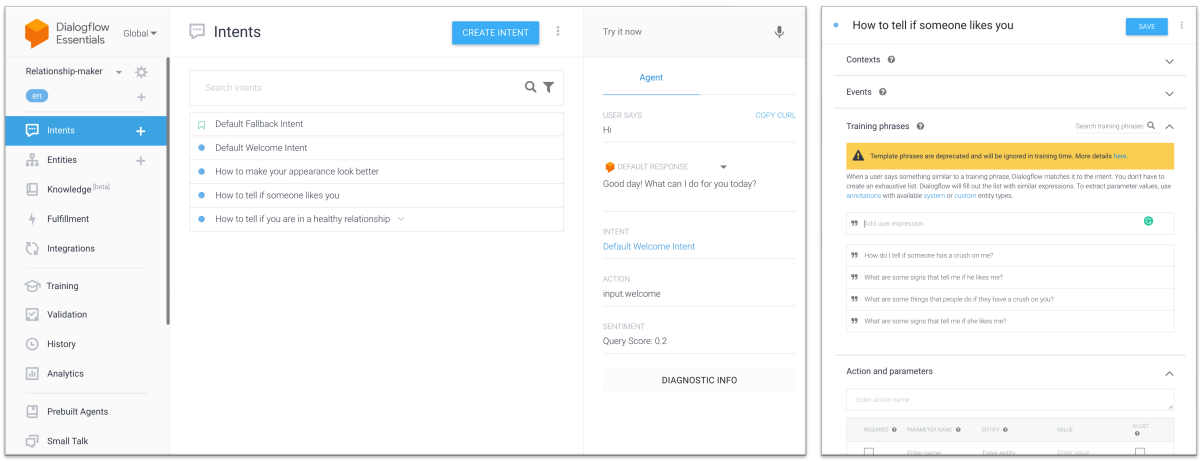


Figure 3-3. Dialogflow interface; Left: main development page for intents. Right: intent editing screen.

- **Overwhelming information from Dialogflow causes frustration**: Dialogflow's screens contain dense text (Figure 3-3), which appeared to contribute to learners becoming bored and frustrated. A substantial amount of their development time was consumed by navigating the interface and locating its relevant features.

- **Difficulty with typing**: Training the conversational AI requires entering a variety of potential user expressions (training phrases) for each intent. We observed that some learners had difficulty typing, which caused frustration and unwillingness to input enough data to effectively train the AI.

3.2 Design Principles and Initial AMBY Interface Mockups

Prior to the contextual inquiry study, we anticipated that young learners would face challenges with Dialogflow. Therefore, in the spring of 2021, in parallel with designing the 2021 summer camp curriculum that utilized Dialogflow, we also worked toward a paper prototype of a novel conversational app development environment for youth. Through a series of discussions within the research team and consultation with external advisory members, we derived four design principles from the existing literature on AI for K-12 and interface design for youth. These design principles guided us throughout the entire design cycle for the alternative interface, which we detail in Sections 3.2 through 3.5. The design principles were as follows:

1. **Foster an accurate conceptualization of conversational AI.** Some related work

suggests strategies to introduce young learners to machine learning [21, 151] and natural language processing concepts [31, 13, 53]. Similarly, as learners create and tinker with conversational AI, the system should represent AI concepts accurately, such as the importance of training data and design of conversational flow [81].

2. **Embodiment of AI agents.** Embodiment of a virtual agent can significantly improve children's engagement in a learning activity [15, 100, 56, 50]. Customization of the agent's embodied characteristics, such as gender, skin tone, and voice, can enhance learner's identity [64] and create a better sense of belonging, thus encouraging youth to engage more with the system [106]. However, agent customization options can also distract from the learning activity itself [75]. We therefore sought to balance the freedom of customization with the core cognitive tasks (e.g., designing the dialogue, creating intents, entering training phrases) afforded by the interface.

3. **Simplicity and age appropriateness.** Younger learners face lower cognitive load and report a better user experience when presented with large design elements [48], simple and intuitive displays [143, 123, 18], and concepts that are conveyed visually rather than with dense text [99, 70]. Thus, we aim to keep interface elements simple and interactive to maintain youth's attention.

4. **Flexible input modalities.** Research finds that interfaces supporting multimodal interaction are preferred over unimodal interfaces because of their flexibility to adapt to user needs [115, 45]. Multimodal interaction is especially beneficial for users developing conversational agents [116]. Our interface follows this path to provide flexible input methods (e.g., typing and voice) to improve input efficiency and adaptivity.

Drawing from the above design principles, especially the agent embodiment and simplicity, we drafted two initial interface mockups (Figure 3-4). The two interface mockups pared down the information in DialogFlow and displayed it in graphical form inspired by Blockly[4]. To elicit feedback from learners on these initial interface designs, we presented

4 https://developers.google.com/blockly

them as paper-based mockups in focus groups at the end of the 2021 summer camp. Each focus group, which comprised 3-4 youth participants, was moderated by one camp facilitator and was audio-recorded. These recordings were subsequently transcribed manually for analysis. Initial open coding of the responses was performed independently by one researcher, who then engaged in a collaborative discussion of the emerging themes with the other researchers during a group meeting.

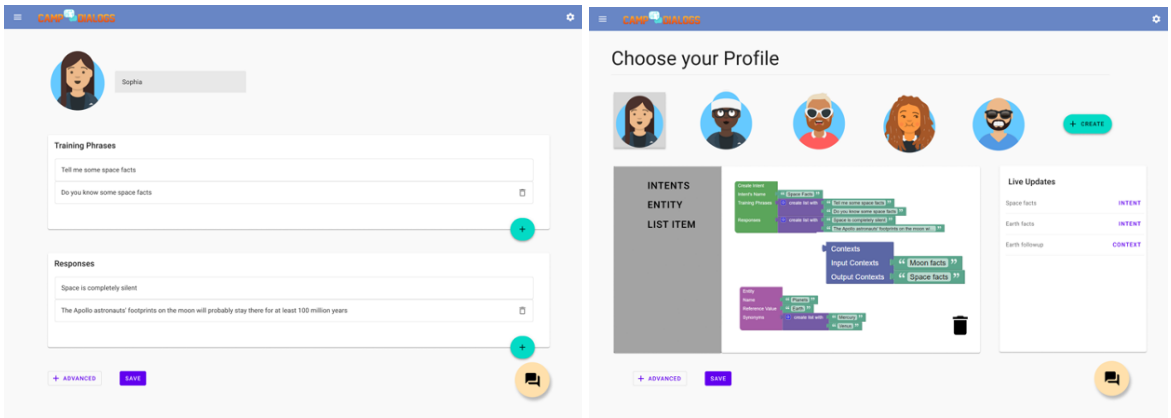


Figure 3-4. The two interface mockups used during the focus group in the contextual inquiry study (Study 1)

3.2.1 Findings from AMBY Paper Prototype Focus Groups

In focus groups, participants spoke to a desire for a streamlined interface that supported agent avatar customization. When discussing the simplified Dialogflow-inspired mockup (Figure 3-4 left), many participants agreed that such a simplified interface would help them focus on creating their agents. When considering the block-based interface (Figure 3-4 right), learners who had prior experience with block-based coding felt the interface could require more time to learn for users without such experience. For both mockups, learners were able to identify key features and functions. All the participants expressed interest in the option to select an avatar to represent their agent.

3.3 Study 2: Cognitive Walkthrough with Adult Reviewers

Based on the findings from the contextual inquiry and paper prototype focus groups, we iteratively refined a series of wireframes using feedback from our entire team, including camp facilitators, K-12 instructional designers, and university researchers in computer science and educational technology. We used these wireframes to implement the first prototype of AMBY,

and then conducted a cognitive walkthrough study. A cognitive walkthrough is an expert review method in which interface experts simulate users "walking through" a series of tasks to identify potential issues and new system features [71, 85].

The 11 cognitive walkthrough reviewers included 8 members of the authors' HCI research lab and 3 researchers specializing in educational technology and computer science education (note that the cognitive walkthrough reviewers' association with the authors may have limited their willingness to provide honest feedback). Among the educational technology researchers, two had over 20 years of experience in instructional design and technology for youth, and the other had 3 years of experience in the field. The HCI team comprised two senior researchers each boasting 15 and 8 years of experience in HCI and dialogue systems research, three with over 3 years of experience, and another three with more than 1 year of experience. Out of these HCI researchers, 6 had done graduate coursework on dialogue systems and had experience developing conversational agents using modern dialogue system frameworks. Though non-representative users, these reviewers were able to use a conversational agent development interface to perform tasks that a typical interface user would need to accomplish, thereby identifying potential design and usability issues.

The cognitive walkthrough study was conducted online through Zoom and lasted approximately one hour. Each reviewer was guided by one researcher to complete four think-aloud tasks using AMBY. The tasks were as follows: create an agent of their choice; edit an existing system intent (the "greet" intent); create a new intent; and create a follow-up intent. In the post-task interview, participants discussed the challenges they faced during the tasks and provided feedback on different interface elements. After the study, researchers discussed their observational notes until they arrived at a consensus on key user needs.

Users encountered no major issues with the fundamental design of the interface and could complete all development tasks within the study's timeframe. Reviewer feedback was used to improve the visual design, such as giving the system default intents unique colors and positions for better clarity, and to simplify the interface text and improve linguistic consistency, as well as to improve usability with functionalities like alert messages and a button to "clear" the chat transcript in the testing panel.

3.4 Study 3: Usability Testing with Young Learners

We updated AMBY prototype 1 based on the cognitive walkthrough study. To assess the usability of the updated prototype (prototype 2), we proceeded to conduct a think-aloud usability study with representative users.

The participants were nine middle school learners who had attended the summer camp in 2021. Former participants were recruited because they were familiar with the fundamentals of conversational agent development.

The study was conducted as an after-school, two-hour, in-person workshop located at a youth educational center. The study procedure was similar to the cognitive walkthrough study, with the consideration that the tasks would take more time for youth to complete than for adults. Before starting the usability tests, participants were given a 20-minute refresher lesson that reviewed necessary conversational AI concepts. After the refresher lesson, participants were then divided into small groups to complete the tasks, guided by researchers. Each researcher guided one or two participants during the session. Participants' interactions and post-task interviews were both screen and audio recorded, with parental consent and learner assent.

During the post-task interview, participants reported liking the AMBY interface's aesthetics. They suggested adding more avatar choices including a way to customize the agent's voice to convey an emotion or embody a character. All participants were able to finish the task in the allotted time. We noted a few common difficulties: it was not clear to learners that progress would be lost when exiting the intent editor if "Save" was not clicked, and learners had trouble distinguishing the training phrase and response entry fields from one another. We modified the system's behavior and visual design to alleviate the identified issues.

3.5 AMBY: A Conversational App Development Environment

In this section, we present the final prototype of AMBY. We describe the system features and the technical implementation of the software.

3.5.1 AMBY 1.0 Prototype Features

When users first login to AMBY, they land on the Dashboard (Figure 3-5, left), where they can (1) create a new AI project, (2) import an AI project from local files, (3) open

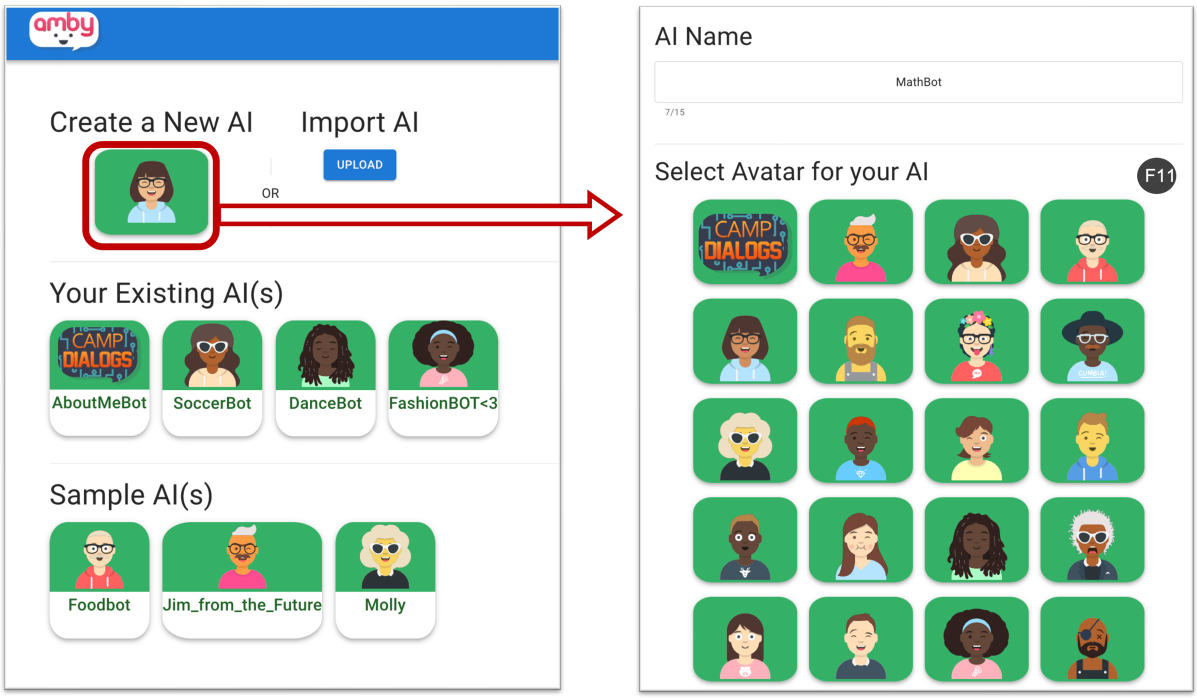


Figure 3-5. Left: AMBY dashboard page. Users can create or import a new agent, select an existing agent, or tinker with sample agents. Right: The agent creation window with a collection of avatars that the learner can choose from. Based on focus group insights, avatars anchor the user's first experiences upon launching AMBY.

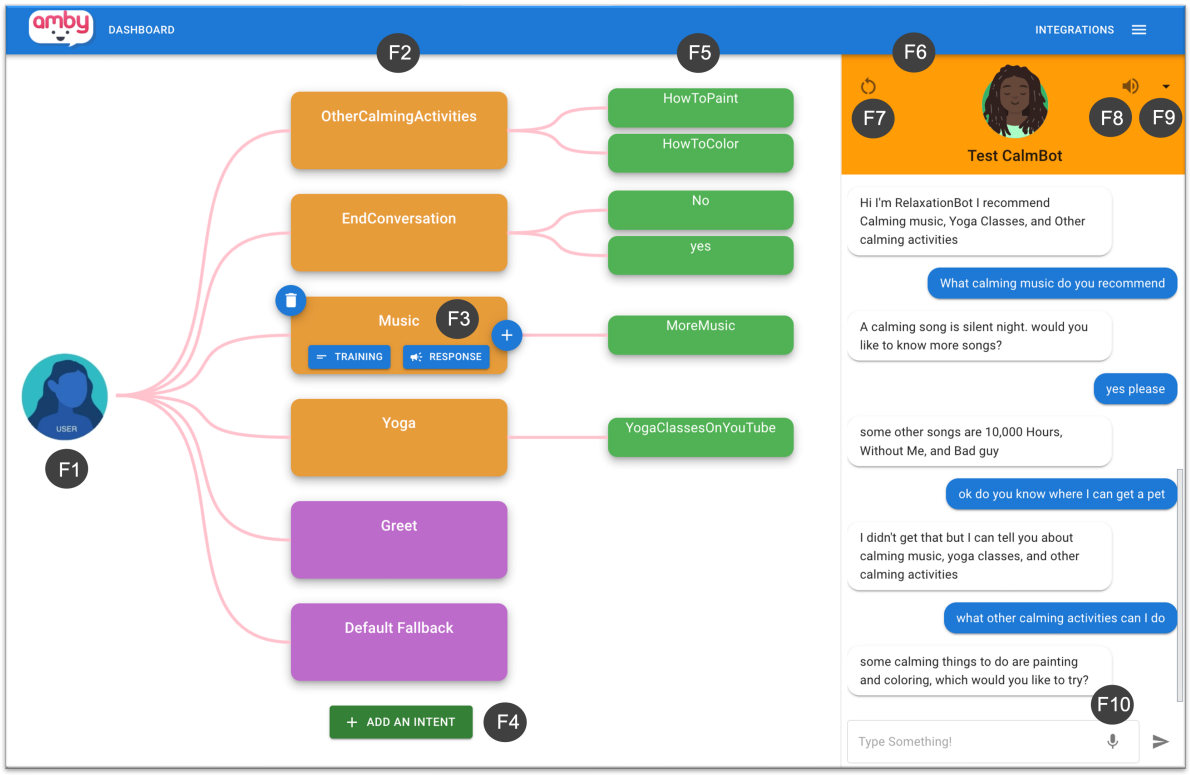


Figure 3-6. AMBY playground page. F1-F10 depict specific interface elements, which are detailed in Section 3.5.1.

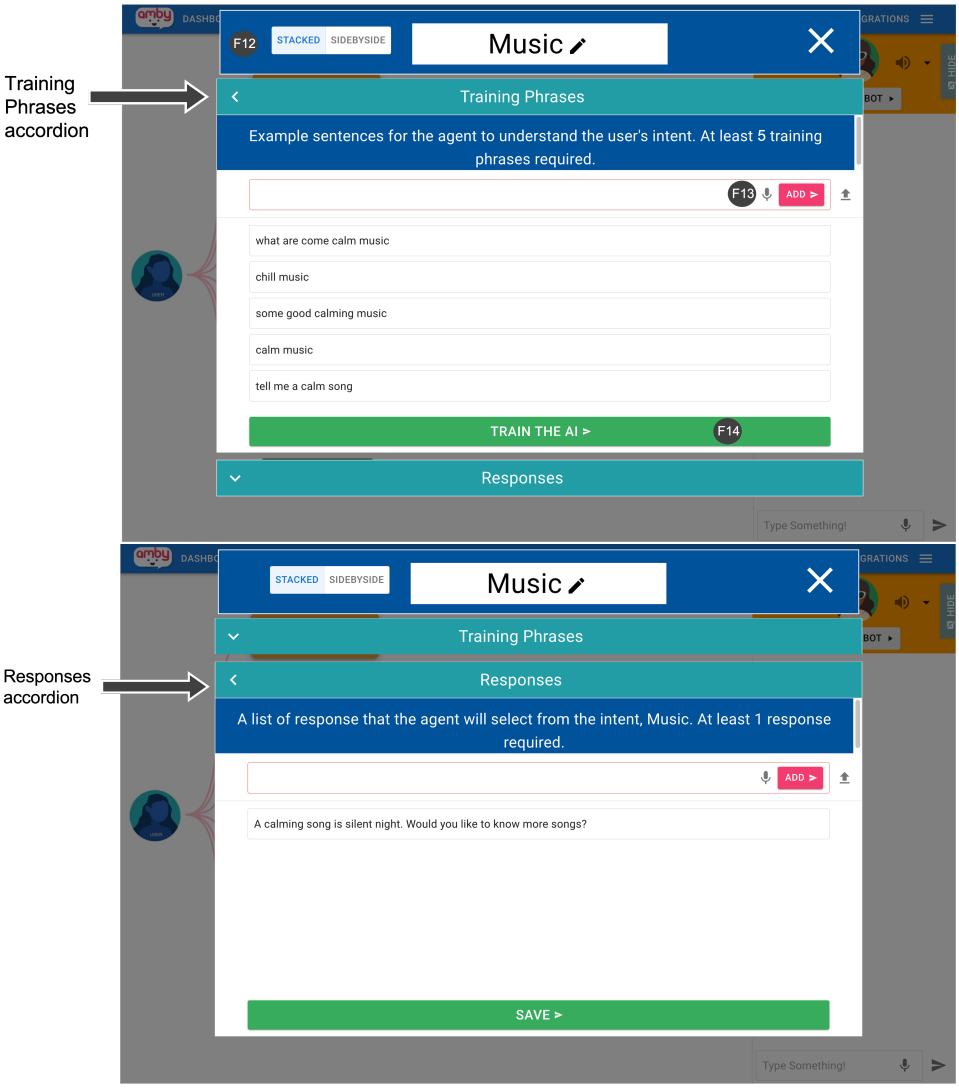


Figure 3-7. Intent editing window (stacked view) for training phrases and responses

previously created projects, and (4) open sample projects available on the website. If they opt to start a new project, they first select an avatar to represent it (Figure 3-5, right). Once the user has selected or created a new project, they are then directed to the Playground page (Figure 3-6), where they can develop, and test their agent. From the Playground page they can also deploy their agent on a Google Assistant-compatible device.

Choice of avatar selection for conversational agents. Although an avatar is not required to deploy a conversational agent on most smart speakers, such embodiment can be helpful for youth to design persona and enhance engagement [15]. AMBY provides a menu of avatars (Figure 3-5) for the users to represent their agents. There are 19 human avatars of different ages and genders and with different skin tones, clothing, accessories, and facial

expressions. There is also one non-human avatar, a logo of the summer camp.

Visualization of dialogue flow. AMBY allows users to create a conversational agent simply by specifying intents, training phrases, and responses. The main development page (Figure 3-6) utilizes a card-based tree design to visualize the dialogue structure (as opposed to a block-based development environment). The conversation tree begins at the end user[5] (F1) and branches out first into the main intents (F2), one of which the end user must invoke before any of the follow-up intents (F5) can be activated. By including the app's end user in this representation, we aim to emphasize the conversational AI concept that intents represent the end user's implicit or explicit goal at any moment in the conversation.

Intents in the tree are represented by simple cards labeled with the intent's name. Options for interacting with an intent card (F3) appear on mouseover. User-generated intents are colored yellow (for main intents) and green (for follow-up intents). AMBY is built on Dialogflow, which generates two default intents ("greet" and "default fallback") that serve special purposes and have unique properties, so these intent cards are colored differently (purple). Follow-up intents (F5) can only be added to a main intent by clicking the "+" button on the right. Once these follow-up intents are created, they are visually connected to their parent intent, rather than directly to the end user, indicating a conditional conversational flow. AMBY users can create an unlimited number of main intents and a maximum of three follow-up intents per main intent. We limited the number of follow-up intents to support a simple visual design and encourage learners to be more strategic about designing the flow of their conversational app.

Intent editing window. When the user clicks the "Training" or "Response" button on an intent card (F3), AMBY displays an intent editing pop-up window, or modal (Figure 3-7). Inside the modal, the user can add, edit, or delete training phrases and responses for the specific intent. Users can toggle how training phrases and responses are displayed in the modal (F12): side-by-side or vertically stacked.

AMBY requires users to enter at least five training phrases before the intent can be saved. This is in alignment with our design principles: while Dialogflow has no minimum

5 In this paper, "User" refers to youth who are developing a conversational AI using AMBY. "End user" refers to a person who is interacting with or testing the conversational AI the youth built.

requirement, AMBY seeks to foster AI understanding by encouraging learners to generate multiple variations of potential user expressions, which also helps minimize the frustrating experience of diagnosing under-trained intents. On the other hand, too many required training phrases could create a situation where learners struggle to generate enough linguistic variations. The five-phrase minimum is a compromise between highlighting the importance of good training data and accommodating the language level and patience of youth.

Agent training/learning animation. We use animation to visualize the agent "learning" from the training process. In the intent editing modal (Figure 3-7), once learners have entered at least five training phrases, they can click the "Train the AI" button (F14) to save their changes. When a learner clicks "Train the AI", AMBY shows an animation (Figure 3-8) in which the agent's avatar is gradually encircled by a progress ring. When the ring is filled, a light bulb appears above the avatar's head, conveying that the agent has successfully learned the new training phrases. No animation is shown when saving responses, to illustrate the distinction that the machine learning model *learns* from training phrases to recognize similar expressions, but repeats response(s) exactly as the developer has entered them.

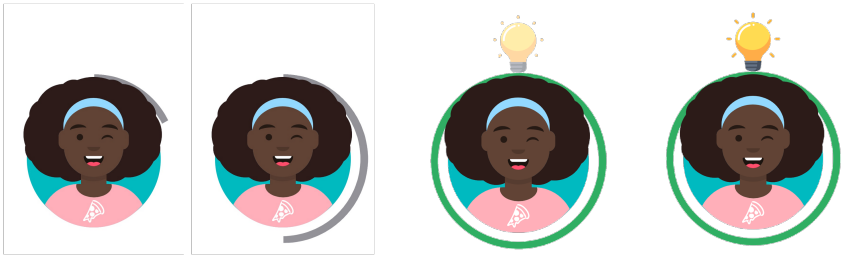


Figure 3-8. The agent learning animation (triggered by the "TRAIN THE AI" button (F14) in Figure 3-7)

Testing panel. Following from common block-based programming environment designs (e.g., Scratch, Snap*!*), the testing panel (similar to an output console or "stage") is on the right of the screen (F6, Figure 3-6). Users can test the agent instantly while editing the intents. The testing panel contains the avatar of the user's agent, a *clear chat history* button (F7), a *mute/unmute* button (F8), and an agent voice customization drop-down menu (F9). In the user text entry box, there is a microphone button (F10) that enables voice-based interaction.

Voice as an input modality. We observed that for some learners, typing was a barrier to using Dialogflow (see Section 3.1.3). Thus, AMBY supports voice-to-text as an input

modality. When entering training phrases, system responses, and "user" dialogue for agent testing, learners have the option to use voice-to-text by clicking a microphone button on the screen (F10, Figure 3-6 and F13, Figure 3-7).

Agent voice customization. In response to feedback from usability testing with returning participants (Study 3), where it stood out as a desired feature, AMBY provides features for the user to customize their conversational agent's voice (Figure 3-9). The voice can be customized along three dimensions: gender (male or female), pitch (-20 to 20 semitones), and speech rate, or speed (0.25 to 4).

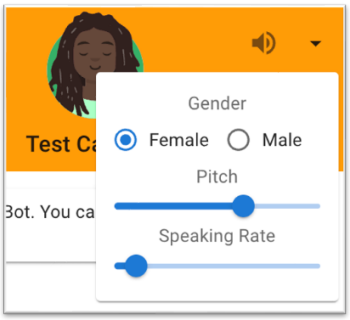


Figure 3-9. Voice customization drop-down menu

3.5.2 Technical Implementation

AMBY is an interactive web application built as a user interface for Google's Dialogflow, which has a robust natural language understanding model, publicly available APIs to facilitate conversational AI management, features for speech and voice modulation, and connectivity with Google Assistant compatible smart speakers and devices. AMBY is developed using the MERN stack (MongoDB, ExpressJS, ReactJS, and NodeJS) and consists of four main components (Figure 3-10): client-side (front-end), Dialogflow interactions, server-side (back-end), and database[6].

The React-based front end handles user login and allows users to see, manipulate, train and test their conversational app. A user's conversational app itself is constructed behind the scenes in Dialogflow; AMBY's front end communicates with Dialogflow using Google's

6 The technical implementation of AMBY was mainly done by Amit Kumar, John Tran Hoang, and Sunny Dhama, all from the University of Florida. Their technical contributions were invaluable to the development of AMBY and the facilitation of this research. My role primarily involved leading the design of the user interface, interaction workflows, and feature prototypes, alongside architecting the database for interaction logs.

publicly available APIs. Once the user has trained their conversational AI, the app can be deployed to a Google Assistant-compatible device in a few steps.

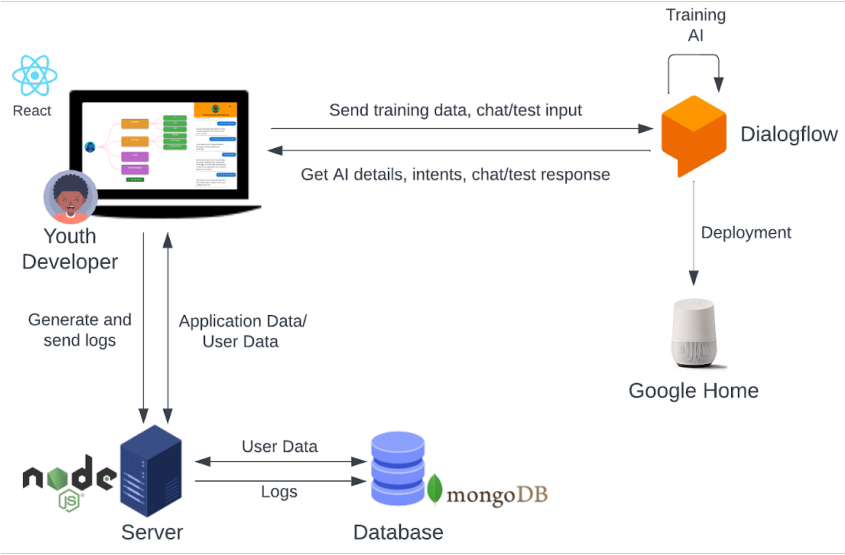


Figure 3-10. Technical implementation architecture of AMBY

CHAPTER 4
PHASE 2: AMBY 1.0 SUMMER 2022 DEPLOYMENT

We deployed AMBY to a two-week AI summer camp where it was extensively used for nine consecutive days. This camp deployment helped us investigate how well AMBY supports youth with little computing background or conversational AI experience as they learn to create their own personally relevant conversational agents, both individually and collaboratively. This chapter is guided by the research question, **RQ2: How do youth engage with a development environment designed to support them in making conversational AI?** I answer this question by analyzing several sources of data: 1) the conversational AI projects learners created using AMBY (Section 4.2.1); 2) learners' experiences using AMBY (Section 4.2.2); 3) learners' usage and perception about the features of the interface (Section 4.2.3); and 4) learners' common challenges using AMBY to develop conversational agents (Section 4.2.4).

4.1 Study Procdure

4.1.1 Participants

In summer 2022, 38 youth (P1-P38) attended the summer camp[1]. Among these 38 participants, 19 identified as female and 19 as male; 31 were Black/African American, five were Hispanic/Latinx, four were White/Caucasian, one was Asian and one prefer not to say[2]. The average age of the participants was 12.7 (SD = 0.7) and all participants were rising seventh or eighth-graders in the upcoming school year. 14 participants (37%) reported having no prior coding experience; 24 participants (63%) reported having experience in at least one type of coding environment such as block-based coding (e.g., Scratch), robotics (e.g., Lego Robots), or text-based coding and app programming (e.g, App Inventor). Among these learners, five had attended the project's summer camp in 2021 (study 1); one attended both the 2021 camp (study 1) and the usability testing (study 3). All parents completed consent forms for data collection prior to camp, and learners provided assent at the start of camp.

1 We host two camp sessions in summer 2022, 17 youth participated camp session A and 21 participated session B.

2 Participants could identify as more than one race/ethnicity.

Figure 4-1. Left: Learners work on their individual projects, mentored by a camp facilitator. Right: Learners work on their paired project.

4.1.2 Study Description

AMBY learning activities spanned eight days over two weeks of the camp. Learners followed a "use-modify-create" progression approach [73] with AMBY. Specifically, on their first day using AMBY, learners used example projects created by the camp facilitators to become familiar with the AMBY interface. On the second day, they learned to modify an example project, "About Me Bot," so that the bot would tell its users fun facts about themselves (the learner). Then, they were guided step-by-step to create a conversational agent from scratch. On days 3 and 4, the learners developed their individual projects with hands-on help from camp facilitators. Beginning in the second week (days 5-8), they worked in pairs to develop another conversational agent relevant to both partners' interests. At the end of the camp, learners showcased their projects to their peers and family members on the Google Home Mini device.

4.1.3 Data Collection and Analysis

During the camp, learners were introduced to design thinking and engineering design processes [126, 10]. We provided a **design log document** (Appendix A) in which learners were asked to articulate their design ideas in seven steps: empathize, define, ideate/brainstorm, prototype, test, modify, and share. We used these documents to extract the ideas and themes found in the learner-created projects.

AMBY also collected **logs of learners' interactions** with the interface. Relevant log actions reported in the paper included: 'create a new project,' 'create a new intent,' 'press the microphone button to enable voice-to-text,' and 'send messages to the agent.' We used the log

data to better understand how learners used AMBY's features and their challenges.

We conducted individual **interviews** with 13 learners from camp session A who attended on day 4 when individual projects were completed. Each interview lasted about 15 minutes and focused on their experience using AMBY for their project and their perception of the embodiment of their agent. On day 8, after learners finished their paired projects, we conducted 30-minute focus groups. We asked 15 learners (three or four per group) about specific features of the interface and solicited suggestions for improvements. Both interviews and focus groups were audio-recorded and manually transcribed by researchers.

We utilized a content analysis approach [55], specifically an inductive coding process [34], to analyze the interview and focus group data. This method is prevalent in HCI literature [24, 59, 63]. First, one researcher (primary coder) conducted open coding on all of the transcripts. Then, the primary coder met multiple times with another researcher (secondary coder) to review and discuss the codes and resolve any disagreements. Finally, the primary and secondary coders worked together to derive themes from the codes until they reached an agreement. The results of this data analysis speak to learners' experiences and their challenges using AMBY.

4.2 Findings

4.2.1 Conversational Agents Created Using AMBY

In total, learners used AMBY to create 25 conversational AI projects, including 18 individual projects and 7 group projects. Each project's name and the description provided by its creator(s) are shown in Appendix B-1. Projects were clustered into themes, using the answers learners wrote in the provided design document template (e.g., Who will use this app? What will this app do?) as well as the conversations their chatbots facilitated. The six major themes were as follows: fashion/shopping, personal/joke, mental health/boredom, educational/knowledge, sports/hobby, and task-oriented. Note that one chatbot may belong to multiple themes. For the scope of this paper, the lead author categorized the projects.

Among these projects, we select two examples that illustrate how learners were able to express themselves using conversational AI.

Example 1. Black History. This conversational agent, named Jerry Berry, was built

collaboratively by two African-American male learners, to teach people about black history and influential black figures including Martin Luther King Jr., Barack Obama, Al Green, Harriet Tubman, and Rosa Parks. During their project demo, they shared the motivation for their conversational app idea:

> *"... Our design represents black power. Black power is something we need..."*

In addition to populating intents with historical facts, the learners also effectively utilized conversational markers to achieve a more natural user experience. For example, they broke up the description of each historical figure across multiple intents. The pair used a connecting phrase, "Would you like to know more?", at the end of each agent response, and provided the follow-up intents to handle "Yes" or "No". Their conversational agent also contains intents that handle social utterances, such as "thank you" and "bye", and an intent handling requests for "help" that describes what the chatbot can do and directs the user in how they might start a conversation. These learners showcased their strong conversational design skills in this personally and socially relevant project.

Example 2. Supporting Mental Health. This was a popular theme, addressed by five of the learners' projects. Many of these aimed to talk to people about their feelings and gave advice on coping with different emotions. Learners said they created the projects mainly due to their personal experience dealing with emotions as middle schoolers, but one learner also indicated its relevance to her career goal. P16 (female) created the conversational agent "ReachOutAndGrabaHand" with the capability to talk about negative emotions (e.g., angry, sad) and give advice on communicating with a partner. She stated that

> *"I created a therapy bot because when I grow up, I want to be a therapist ... [People would like] having a robot that's programmed to be a nice human, instead of judging. It's easier to talk to that instead of talking to a person that can go back and tell someone [else]."*

These youth were able to use conversational AI to explore and express empathy and think about solutions to salient problems in their lives.

4.2.2 Learners' Experiences Using AMBY

Here, we report on the learners' comments in focus groups and interviews.

Overall engagement. Overall, learners enjoyed using the tool to create conversational agents on their own. They expressed that AMBY gave them the freedom to create their personally relevant projects. In two participants' words:

> *"It lets you choose the responses ... how it lets you do what you want to and that it doesn't tell you what to do."* - P7 (female)

> *"[I like] creating and adding the intents because it's fun to make your chatbot respond to anything."* - P11 (female)

Learners also mentioned that they liked the testing window on the interface, which allows them to test on the fly.

> *"I like that you can add your own intent and you can test it right away to make sure it works."* - P4 (male)

Five learners from this study also attended the camp in the summer of 2021. All felt that using AMBY was easier and more engaging than Dialogflow. One returning participant, P2 (male), created his chatbot to be a representation of his own appearance and personality. Over the course of the camp, he had put significant effort into developing his individual agent and stated that in AMBY, *"the avatar, the voice, everything"* were better than the Dialogflow interface he had used the previous year.

Control over the AI. All the interviewed learners thought the agent they created was intelligent, and that because they were the ones who added (e.g.) *"information"*, *"knowledge"*, *"questions and answers"*, *"A lot of training phrases"*, or *"more intents"*, they were also in control of the agent's intelligence. P15 (female) mentioned that she *"made it smarter by adding wrong spellings of certain words, so it would still recognize it"*. P13 (female) emphasized the agent's machine learning ability and said she believed that *"if you work on it enough, it could be smart enough to work on its own."*

4.2.3 Learners' Usage and Perception About the AMBY Features

Agent embodiment: Voice customization. Of the 13 learners interviewed, 11 had used the voice customization feature. Six reported that customizing the agent's voice was helpful in conveying its personality. P2 (male) said, *"If you want it to be funny, you give it a high pitch voice"*, while P11 said that to show her agent's *"nice and caring personality"* she decided to *"make it a very soft, squeaky voice."* Further personifying her agent, she also represented excitement in her agent by adding emojis to its text responses:

> *"I made it speak with a bunch of emojis so the user knows what the bot is feeling.*
> *"* - P11 (female)

Agent embodiment: Avatar selection. When asked why they chose a specific avatar for their project's agent, 7 learners reported they picked the avatar because it looked similar to themselves; 5 reported they picked the avatar based on their target end user (e.g., P16 chose the "pirate"-styled avatar with an eye patch for her therapy bot, "ReachOutAndGrabaHand", because she thought *"he would need someone to talk to"*). One learner reported that they had picked their avatar at random.

Voice-to-text feature usage. Next, we investigated how learners used the voice-to-text feature in AMBY for authoring and testing the conversational agents (F10, Figure 3-6 and F13, Figure 3-7). Across 18 individual projects, we found 12 projects used voice-to-text for sending testing messages, six for creating responses, and three to create training phrases.

Although the voice-to-text feature was not used by all learners, it did significantly address some specific learners' needs. For example, one learner (P6, male) utilized voice-to-text frequently for training phrases, responses, and chat testing for both his individual and paired projects. Using the voice-to-text feature, he entered almost twice as many testing messages by speaking (65 messages) as he did typing (34 messages).

4.2.4 Common challenges using AMBY to create conversational agents.

While learners enjoyed the creative freedom of their projects, their most commonly reported challenges also stemmed from the creation of content for the agent. For example, P3 (male), who made a boxing coach agent, said, *"I had to search up things about boxing to use it on AMBY."* P7 cited *"the fact you have to write a lot"* as a difficulty: she had made some

revisions that required her to rewrite many training phrases and responses. Generating ample, sufficiently varied training data to recognize each intent was also reported as a common difficulty. P8 (female) said her biggest challenge came from,

> *"knowing what the user was gonna say, and word[ing] it a bunch of different ways for training phrases."*

Another challenge for the learners was interpreting the intent classification failure. When the agent cannot confidently match a user utterance to an existing intent, the only output the tester receives is the default fallback response. It is up to the developer (the learner) to infer what has gone wrong, and many learners found the limited feedback to be a frustrating challenge.

Finally, a number of learners reported problems with system instability such as system lagging or no response. In part, this can be attributed to the limitations of the Dialogflow API for handling high-volume request calls as well as to slow internet speeds at the camp location.

4.3 Discussion and Design Implications

The results from our summer camp deployment suggest that youth learners can successfully create personally relevant conversational agents using AMBY: the projects that learners created using AMBY covered a variety of themes and interests, and learners reported positive experiences during interviews and focus groups, despite also facing challenges. In this section, we discuss the design implications from our effort to create a conversational AI development interface for young learners. We hope these implications will stimulate continuing conversation within the research community about future trajectories for learning technologies that support AI education for youth.

4.3.1 Interfaces Should Be Low-entry, But High-ceiling

Numerous studies have emphasized the importance of offering a low barrier of entry to novice learners [49, 44]. The low-entry interface we designed allowed learners with no prior coding experience to create relatively complex conversational agents, compared to those created in the summer of 2021 by learners using Dialogflow, which was not designed for use by novices, for the same task. In summer 2021, using Dialogflow, the average number of

intents learners created was 4.71 (*SD* = 1.67), consisting of an average of 3.71 main intents and 1 follow-up intent. In contrast, in summer 2022, using AMBY, the first-time learners[3] made 15.88 intents per project on average (*SD* = 11.5), with an average of 9.88 main intents and 6 follow-up intents, which represents significantly more complex projects.

Interfaces that support conversational agent development should also be high-ceiling. Considering the display size of a laptop screen, AMBY only supported two layers of intent (one layer of main intent and one layer of follow-up intent) in this study. Learners suggested adding the capacity for more levels of follow-up intent to meet their project needs. For example, P17 (male) was an advanced learner who wanted to create a tic-tac-toe game. He calculated that implementing this game would require creating 81 total intents, including at least two layers of follow-up intents, which the AMBY environment could not support.

Some literature suggests that responsive interface elements can be more welcoming [9]. Our participants also spoke to this notion, suggesting that AMBY should allow them to collapse and expand subtrees of follow-up intents, or "*move them [intent cards] anywhere, like [from] a [main] intent to a follow-up intent.* (P14)" To employ another common strategy, the interface could be made more flexible by collapsing the advanced features into a different module, and de-emphasizing the advanced module to novice learners; the module might even be "locked" until the learner has completed certain basic tasks in AMBY.

4.3.2 AI Development Environment for Learners Should Be Transparent

A pedagogical system for conversational AI development should be transparent about how the AI represents knowledge and makes decisions. In our context, we directly represent the agent's knowledge by visualizing the dialogue structure, and we reinforce the agent's way of learning implicitly by scaffolding the intent creation process and explicitly with the learning animation. However, our system can be further improved by adding more transparency to the agent training and intent classification processes. As discussed in the findings (Section 4.2.4), one main challenge the learners faced was understanding intent classification. As P7 (female) said, *"it would be helpful to see exactly what the bot does not understand."* Learners reported that it would be helpful for the system to locate intent

3 excluding returning participants, whose prior experience with Dialogflow would likely impact their projects' complexity

classification mistakes and scaffold their understanding of the AI's decision-making process. This design implication maps to AI literacy competencies, specifically those regarding understanding knowledge representation and how computers reason and make decisions [81]. Literature suggests that graphical visualizations and interactive demonstrations of models can aid a better understanding of AI [67]. For conversational AI development interfaces, specific design considerations for transparency would be to include the intent classification results for learners who desire to inspect it. Similarly to existing interactive tools for exploring natural language processing techniques [53, 13, 41], the interface could also highlight important words or phrases which the system weighted more highly in order to aid in learners' understanding of the computer's representation of natural language [92].

4.3.3 Interfaces Should Foster Users' AI Learning Experience

The findings of this study suggest that interfaces should prioritize the ability of users to showcase their knowledge and skills in relevant and meaningful ways through the projects they create. Prior research has shown that people are more likely to identify with a learning experience that is culturally relevant and reflects their community [28]. The projects created by the learners exemplify this. Design features that enable such personalization, such as agent embodiment with avatar selection and voice customization, has facilitated this user expression. For instance, from our study, a majority of learners customized their agent's voice to convey a certain personality, many chose avatars that resembled themselves or were related to the theme of their project, showing the significance of personalization and its impact on user engagement. Beyond personalization, it is also evident from section 4.2.1 that the choice of project themes can stem from deeper, personal or societal motivations. Voice-to-text feature usage offers another insight: interfaces should provide diverse interaction modes for different learner needs. The primary implication here is not just about embedding personalization features, but about deeply understanding and integrating learners' backgrounds, motivations, and experiences in AI learning tool designs. There is a tremendous opportunity for future research to further investigate how learners' backgrounds shape their interactions with AI tools, and how these tools can be refined to foster a more enriched and engaged learning experience.

4.3.4 Interfaces Should Empower Users To Incorporate Multimedia

In the study interviews, many learners indicated a desire to include multimedia in their agents' responses. For example, one participant wanted their agent to be able to provide images and videos to demonstrate the dance moves it was designed to talk about, and two others, both of whom independently created music recommendation agents, said they would have preferred if their agents could play music, rather than simply naming songs. While these are currently beyond the scope of AMBY, working with multimedia has been shown to foster creativity [132] and learner engagement [109], and there has been some research into multimodal dialogue systems [76, 122, 114]. There are existing tools such as Adaptive Cards[4] which may be easy to implement for adding multimedia support; however, such support has to be adapted to youth needs. Future efforts to create conversational AI development systems for youth should consider enabling users to embed multimodal content into agent responses, or potentially even automating connection to appropriate APIs.

4.3.5 Limitations and Future Work

This study has several limitations. First, due to the nature of the summer camp format, we are unable to measure participants' AI learning as a result of using AMBY alone. Although learners used AMBY extensively throughout the two-week session, they also engaged in other types of learning activities. It would be interesting to see how AMBY could be utilized outside of an informal, camp context to support different learning tasks. For example, a middle school science teacher might introduce AMBY in their classroom to assign students to create quiz bots on science content to support learning objectives.

Another limitation is that we did not evaluate the effectiveness of AMBY in a controlled experiment. As mentioned in section 2.3, currently there is no conversational AI development tool that can achieve the same tasks as AMBY that are developmentally appropriate for youth. Our results have demonstrated the extent to which youth created more sophisticated projects using AMBY compared to DialogFlow, but this direct comparison must be taken lightly because DialogFlow was not designed for novices. Our approach to investigating the effectiveness of AMBY follows best practices (such as extracting themes qualitatively using

4 https://adaptivecards.io/

field notes and observations [61], focus groups and contextual inquiry [112]) within the HCI community when an experimental study is not practical.

4.4 Conclusion

This paper has presented the iterative design and development of a conversational AI development interface, AMBY, that supports learners to create and tinker with their own conversational agents. Working in partnership with 26 youths, the interface was iteratively designed and developed through multiple user studies over 14 months. The interface was deployed to a two-week summer camp, allowing the study to engage learners in an informal setting with limited prior computing experience. Our work offers a new alternative to empower youth without an extensive technical background in building authentic AI applications. With continued research, this line of investigation holds the potential to open authentic AI learning experiences to learners of all backgrounds and ages.

CHAPTER 5
PHASE 3: AMBY REFINEMENT AND SUMMER 2023 USABILITY STUDY

In this chapter, I further improved AMBY with additional features to enhance learners' experiences. This study is guided by RQ3, which states: **What features do youth desire in a learning environment to support their educational needs?** My goal for this iteration is to explore learner's initial reaction and their usage on the updated AMBY features. Section 5.1 describes the new features integrated into AMBY 2.0, Section 5.2 presents the study procedure and findings of the user study in Summer 2023.

5.1 Additional Development of AMBY

In the previous studies, learners have provided important feedback on improving the usability of AMBY. A central goal for this phase was to address these suggestions to further enhance learners' experiences. An overview of the additional features for AMBY 2.0 is in Figure 5-1.

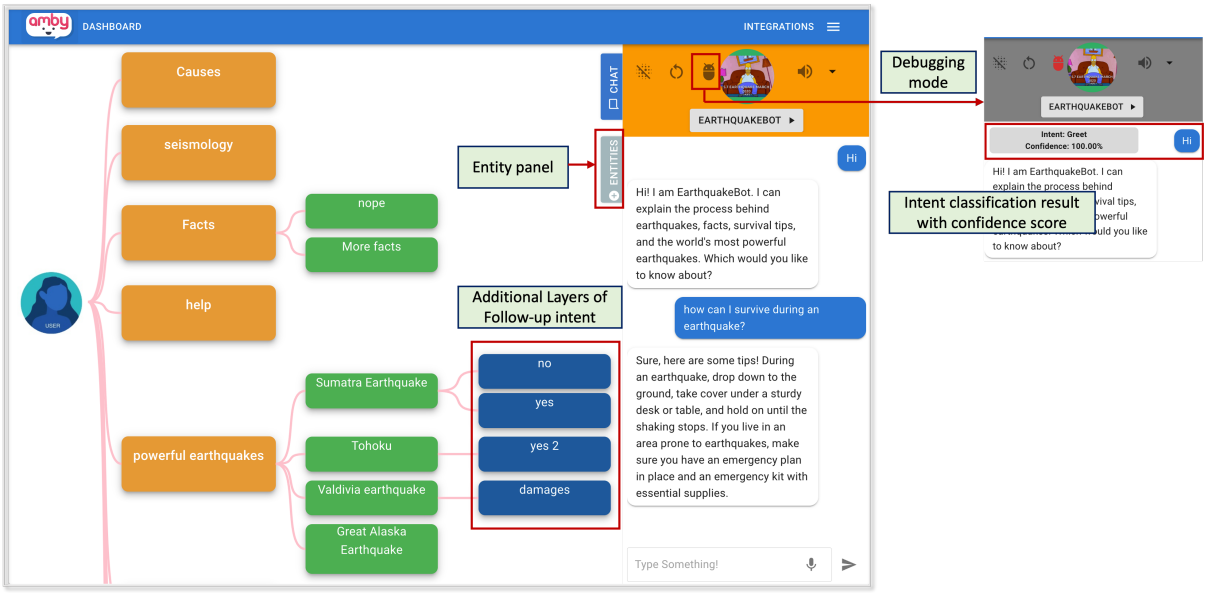


Figure 5-1. Overview of additional features in AMBY 2.0.

Additional Follow-up Intent Layers. Based on feedback from prior user studies (Chapter 4), learners suggested incorporating additional follow-up intent layers to enable more comprehensive conversations. In alignment with the design recommendation of a "high-ceiling" interface (Section 4.3.1), our updated AMBY version now supports up to three intent layers. This enhancement empowers learners to develop more detailed and nuanced conversations for their conversational agents.

Intent Debugging Feature. Drawing from past observations and the design recommendation emphasizing transparency in agent training and intent classification (Section 4.3.2), we have introduced an "intent debugging" feature. This AMBY version provides users with a button to inspect the intent classification outcomes of user utterances, along with the confidence level of such classifications. To activate the debugging mode, users simply click on the bug icon adjacent to the avatar in the chat simulation panel. When this mode is on, the chat panel's top banner changes to a grey shade, highlighting its developer-oriented nature. Hovering over individual user utterances will then display a popover, detailing the intent classification result and its associated confidence level.

Entity feature. A recurring challenge identified by participants in past studies was the tedious process of entering numerous training phrases. They frequently pointed out the monotony of inputting similar training phrases for different intents, which often resulted in user frustration. Some learners expressed interests in further expanding their project visions by incorporating more personalized responses based on user utterances.

In response to these feedbacks, and with an aim to expand the use cases of AMBY, we introduced the "entity" feature. An entity consists of words or phrases extractable from user input[1]. For instance, if a user requests, "Tell me the flight information from Orlando to Atlanta," the intent "flight information" is activated, while "Orlando" and "Atlanta" are identified as the "location" entity. The introduction of the entity feature yields two primary advantages:

1) It significantly streamlines the training process by eliminating the need for repetitive entry of similar phrases. In the absence of entities, developers would need to input every possible combination of locations for the "flight information" intent. Entities introduce a more efficient approach; rather than tediously substituting the noun or verb in each training phrase, developers can concentrate on developing diverse linguistic variations of the phrases. This not only saves time but also enhances the overall quality and diversity of the training dataset.

2) Developers can construct more personalized responses based on user utterances. In

1 In Dialogflow's original definitions, there are two distinctive definitions of 'entity types' and 'entity entry'. To teach middle school learners and consider the use cases of our system, we simplied the two terms to one "entity" term. https://cloud.google.com/dialogflow/es/docs/entities-overview

the past, responses can only be hard-coded by the developers thus might have been generic, such as, "*There are three flights for the cities you mentioned.*" With the new feature, a more specific reply such as, "*There are three flights from Orlando to Atlanta today*" becomes feasible. This enhances the end-user experience, as the agent can directly address and confirm user-specific details.

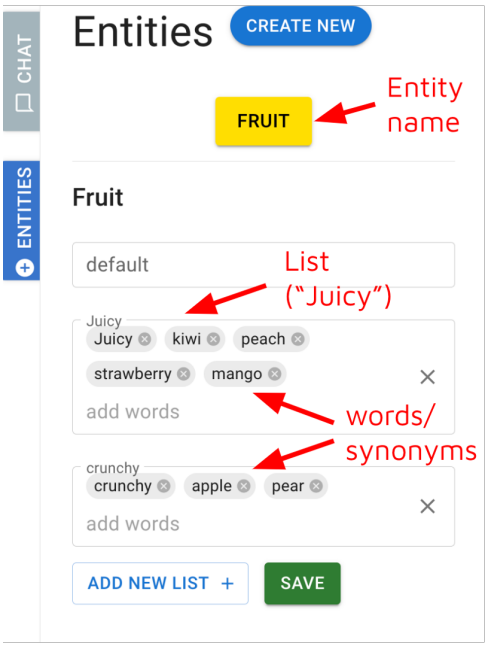


Figure 5-2. AMBY entity creation page.

Developers can navigate to the entity feature by selecting the "entities" button located on the right panel. This position is designed to replace the chat simulation panel during the entity setup phase (expecting few testing requirements during this process). The entity setup interface is shown in Figure 5-2. Here, developers can formulate a new entity and, if desired, append entity lists (entity sub-categories, there is a default list). Within each list, synonymous words or phrases can be grouped (e.g., "kiwi" and "mango" are categorized as "juicy" fruits). After the entity creation, they can be integrated into the intent. Figure 5-3 shows how to incorporate entities within training phrases and responses. In the training phrases window, inputting a $ symbol prompts a dropdown of available entities. Once an entity is selected, it is highlighted in yellow with an underscore, representing its distinctive nature. Any word or phrase within this entity is treated equivalently during training. When the intent is activated based on user input, relevant entity data is extracted and can be incorporated into a customized

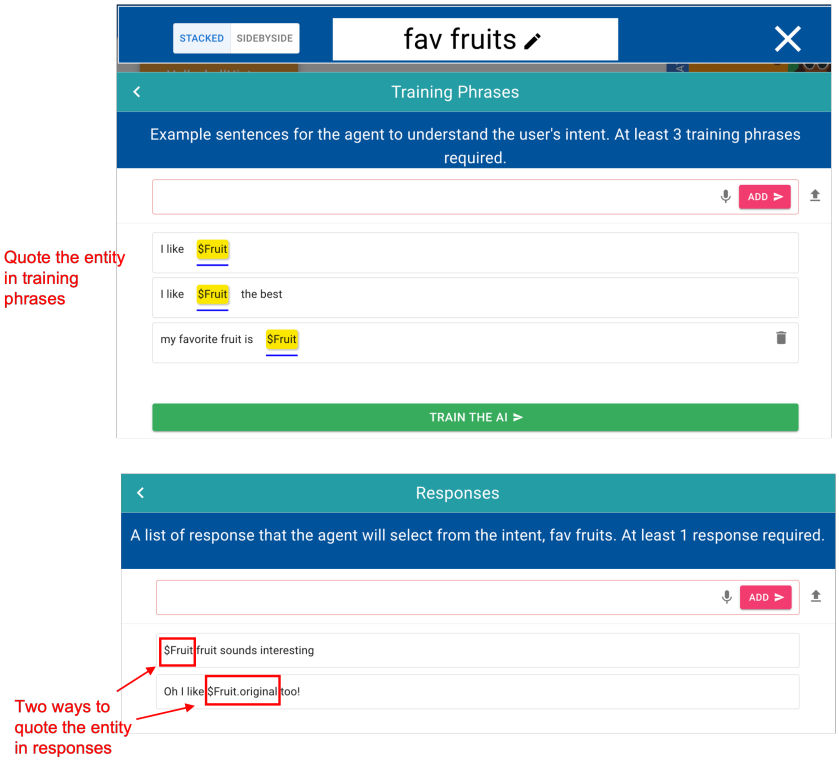


Figure 5-3. Interfaces to quote the entity within an intent. In this example, 'fav fruits' intent can recognize different kinds of fruits through the "Fruit" entity. It can produce personalized response based on the user's utterance. For example, if the user says: "I like *apple* the best. ", The agent would respond either as "*Crunchy fruit* sounds interesting" (because 'apple' was set to fall in the 'crunchy' list of the 'Fruit' entity) or "Oh I like *apple* too!"

response using the "$name" or "$name.original" syntax.

5.2 Summer 2023 Study

To teach the concept of entities at the summer camp, I developed a new lesson centered around the entities. This lesson was first piloted during professional development sessions with the camp facilitators before the camp started. Given that this topic is an advanced learning concept, it is structured to be introduced to learners only after they have acquired some developmental experience with AMBY. In Summer 2023, the "Entity" lesson was introduced to learners on the morning of the seventh day of camp. By this time, the learners had already gone through all the scheduled camp lessons, completed an individual project, and had made some progress towards a collaborative project.

In summer 2023, 19 participants attended the summer camp. Among these 19 participants, 7 identified as female and 12 as male; 8 were White/Caucasian, 6 were Black/African American, 4 were Asian and 2 were Hispanic/Latinx. The average age of the

participants was 12.05 (SD = 0.4). 14 were rising 7th-graders and 5 were rising 8th-graders in the upcoming school year. During the camp, we conducted one-on-one interviews with 16 participants at the end of camp day 5, where they just finished their individual projects. We also administered two focus groups on the perception and usage of the entity feature on camp day 7. This was after introducing them to the concept of entity and providing several sessions throughout the day to work on a second project. Both interviews and focus groups were audio-recorded and transcribed for analysis. I used the same content analysis approach for analyzing the interview data as detailed in Chapter 4.1.3.

5.3 Preliminary Findings on Entity Feature Perception and Usage

The majority of participants were familiar with the concept of an entity. When prompted to provide a definition, three of the learners described it as akin to *variables* in programming that can hold various values or words.

"*(It's) like a variable on Scratch. It can hold different meanings for it but using just one thing.*" (camper101)

Most of the participants acknowledged the utility of the entity, noting that it "*allows you to use way less training phrases and make the response more personalized for people.*" (camper 109). They believed it was beneficial in improving the efficiancy of their development work.

Regarding the usage of the feature, among the 17 participants, four (camper 101, 109, 120, 122) stated that they incorporated the entity feature into their group projects. Notably, both teams developed interactive games: one modelled after the popular American quiz show "Jeopardy", and the other named "PokeGameBot", which simulated a Pokémon battle. Both games employed consistent sentence structures across diverse topics (e.g., the answers to the Jeopardy game consistently began with a "What is" phrase). To create more streamlined and diverse inputs, these groups incorporated keywords and phrases into an entity, ensuring they "*don't have to type the same words over and over again.*" (camper123)

"*Instead of typing like, 'Is the answer ___? And/or is it that?' You just put a bunch of stuff for the entity.*" - camper122

Interestingly, both teams found the entity feature to be beneficial primarily for training

phrases, rather than for personalized responses. This indicates that learners recognize the value of entities in off-loading the repetitive aspects of training tasks. By reducing manual input, entities allow learners to shift their focus towards more creative aspects of AI development. Additionally, the preference for using entities in training phrases over personalized responses also suggests the critical role of effective training in the success of an AI application.

During the focus group, four participants admitted to finding the entity feature somewhat "*confusing*". This perception might stem from the feature's inherent complexity and its introduction relatively late in the camp (on Day 7). By that time, many learners had already established their developmental approach with AMBY, and incorporating a newly introduced feature—especially one not initially factored into their project's design—became a challenge. Their initial mental model for development had been solidified.

"*It was a bit confusing and I decided that it would take too long to figure it out. It would be simpler to just go on what I had already been going.*" (camper119)

There was a clear desire among learners for more fine-grained control over conversational design. For example, camper109 suggested the possibility of integrating a customizable default fallback for follow-up intents, thus allowing their chatbots to generate more contextually appropriate fallback responses.

In summary, our preliminary findings from Summer 2023 showed the promise of the entity feature in enhancing learner experiences. Majority of the participants demonstrated an understanding of the entity concept and perceived it as useful tool. Many saw its potential in streamlining and personalizing chatbot training phrases, and a subset even leveraged it heavily in their projects. Despite the entity feature being recognized as an advanced learning topic, our results suggest that its introduction should occur earlier in the curriculum, before they start building their own projects. Doing so would better support learners in establishing effective development routines with AMBY and maximize its utility.

5.4 Conclusion

In this chapter, I have described the refinement of AMBY with three additional features: more follow-up intent layers, intent debugging feature and the entity feature. Through our summer camp study in 2023, I gained pivotal insights into learners' reception and engagement

with the enhanced features, especially the entity feature. These findings emphasize the need for a more rigorous experimental study to assess the feature's effectiveness on a larger scale. Moving forward in Chapter 6, I will focus on deploying AMBY 2.0 in the middle school classroom context and investigating the influence of the entity feature on students' interests and experiences.

CHAPTER 6
PHASE 4: AMBY CLASSROOM STUDY

The previous chapters have described the iterative design and development of the learning environment AMBY and findings from the user studies in the summer camps. In this chapter, I describe our deployment of AMBY 2.0 interface in a new learning setting: middle school science classroom. My primary goal is to examine the impact of the entity feature in AMBY on learners' enjoyment and chatbot project outcome. The research question guided this study is: **RQ3: Does *entity* feature impact students' enjoyment and artifact quality?** Additionally, I investigated the students' attitude change, situational interest, content knowledge of AI as the outcome of middle school science classroom intervention.

In this chapter, in Section 6.1, I first introduce the science-based conversational AI curriculum that I developed for the classroom study. Then, in Section **??**, I describe a detailed research design for the classroom study for AMBY 2.0, including paticipants, study procedure, data collection and analysis. In Section 6.3, I present the results for the entity feature effectiveness and post-hoc analysis regarding the outcomes of the classroom intervention. In Section 6.4, I discuss the findings and implications of this research.

6.1 Science-Based Conversational AI Curriculum

Building on the foundation of the earlier phases of AMBY and summer camp curriculum [120], my next step is to extend its application in a formal classroom context. To transition the learning activities from informal summer camp to classroom settings, we will make adjustments to the conversational AI curriculum.

First, I have condensed the curriculum to fit into an approximately 10-hour learning module, which aligns with the intended duration of the classroom study (Section 6.1.1). Second, I have worked with three middle school science teachers to embed science content in the conversational AI curriculum (Section 6.1.2). The new science-based curriculum contains examples related to the science topics that the students learned previously (such as scientific methods), and the activities are closely tied to their previous science learning experiences.

6.1.1 Classroom AI Learning Modules

The curriculum is focused on teaching students the fundamentals of Artificial Intelligence and Conversational AI in a science context. The course is divided into several

modules, with each module covering specific topics related to AI and conversational agents. The learning objectives are shown in Table 6-1.

Lesson	**Learning objectives**
L1 - Intro to AI	Define artificial and intelligence Identify characteristics of AI (artificial and intelligent) Give examples of AI (such as siri, self-driving cars) and understand what makes the example AI
L2 - Intro to chatbot	Identify chatbot/conversational AI applications (e.g., Siri, google home, Alexa) List examples of what chatbots can do (e.g., answer questions, make recommendations, perform some task)
L3 - Intro to intents	Differentiate the role of developer/user/agent Define intents Identify the components of intents Explain how training phrases work Explain how responses work Identify when the greet intent will be used Identify when the default fallback intent will be used Create customized responses for the greet intent Create customized responses for the default fallback intent
L4 - Follow up intents & Conversational design principles	Define follow-up intents Identify good conversational design practices, including: 1. Setting user's expectations through chatbot greet responses 2. Designing conversational flow through multiple logical follow-up intents in which each follow-up intent is related to its parent intent logically 3. Using conversational markers (such as "Okay", "Thank you") to make naturalistic conversation 4. Guiding the user when there is no match intent through customized default fallback response 5. Having a "help" intent to handle user confusion such as "help", "what can you do" 6. Adding many training phrases
L5 - Intro to Entities	Define entities in the context of conversational AI Identify potential entities from user utterances
L6 - Project development	Demonstrate conversational agent ideas Use AMBY to create a conversational AI project Apply conversational design principles to make naturalistic conversations Test and revise their projects Evaluate others' conversational agents Reflect on what worked well, what did not work well with their conversational agent based on peer testing

Table 6-1. Learning objectives of science-based conversational AI curriculum

In the first module (L1 - Intro to AI), students are introduced to the basics of AI and its characteristics. They learn about the different types of AI and are given examples of AI applications such as Siri and self-driving cars. The learning objectives for this module include being able to define artificial and intelligence, identify characteristics of AI, and give examples of AI.

In the second module (L2 - Intro to chatbot), students are introduced to chatbots and conversational AI applications. They learn about the different tasks that chatbots can perform, such as answering questions and making recommendations. The learning objectives for this module include being able to identify chatbot/conversational AI applications and list examples of what chatbots can do. In this learning module, students will also play with the sample AIs in AMBY.

The third module (L3 - Intro to intent) covers the basics of intents and how they are used in conversational AI. Students learn about the different components of intents, how training phrases work, and how responses work. They also learn about the greet intent and the default fallback intent and how to create customized responses for these intents. The learning objectives for this module include being able to differentiate the role of developer/user/agent, define intent, and create customized responses for the greet intent and the default fallback intent.

The fourth module (L4 - Follow-up intents and conversational design principles) covers follow-up intents and good conversational design practices. Students learn about the importance of setting user expectations through chatbot greet responses, designing conversational flow, using conversational markers, and guiding users when there is no match intent through customized default fallback response. The learning objectives for this module include being able to define follow-up intents, identify good conversational design practices, and create many training phrases.

The fifth module (L5 - Intro to entities) introduces the concept of entities in conversational AI. Students learn to define entities and identify them in user utterances. Students engage in hands-on practices regarding entities in AMBY to understand the benifits of using entities in their conversation. The key objectives include understanding entities in AI

conversations and recognizing their use in enhancing chatbot interactions.

The sixth module covers project development (L6 - Project development), where students demonstrate their understanding of conversational agent ideas, and use AMBY to create a conversational AI project related to the science topics they learned previously. Students also learn how to apply conversational AI design principles to make conversations and test and revise their projects. The learning objectives for this module include being able to demonstrate conversational agent ideas related to science, use AMBY to create a conversational AI project, apply conversational AI design principles, and test and revise their projects. Additionally, after students finish their project, they will engage in peer testing in which students will form small groups and evaluate other's conversational agents. After peer testing and feedback, students will reflect on what worked well, what did not work well with their project and refine their agent based on the peer feedback.

In summary, the curriculum is designed to provide students with a comprehensive understanding of artificial intelligence and conversational AI, with a focus on designing and building conversational agents. Through these lessons, students will learn how to create naturalistic conversations, understand good conversational design practices, and apply their knowledge to create functional conversational agents.

6.1.2 Exemplar Science Chatbots within the Curriculum

For this science learning context, we provide three science agents, *EarthquakeBot*, *Ralph* and *ScienceGenuis* as sample AI agents for students to test on. *EarthquakeBot* is in alignmnet with the *plate tectonic* topic in science curriculum. The agent explains the process behind earthquakes, facts, survival tips, and the world's most powerful earthquakes. *Ralph* engages users with interactive quizzes about random science topics. *ScienceGenuis* is relevant to the *scientific method* unit. This agent is knowledgeable about different scientific methods and steps of scientific methods. These three sample agents serves as examplar projects for students to model for their personal projects. These sample agents follows the best conversational design principles introduced in the later part of the curriculum. We also use examples extracted from these sample agents to reinforce the learning objectives in the conversational AI curriculum.

6.2 Study Overview

6.2.1 Participants

Participants were recruited from a local public middle school. Initially, I contacted the science teacher to discuss the integration of a learning module that aligned with their educational objectives and standards. Upon approval, students from the 6th grade science class were invited to participate through in-person announcements and email communications. Participation in the research study was voluntary. All students in the class were offered the opportunity to engage in the AI learning activities, regardless of their consent or assent status.

The study was conducted in Spring 2024 semester with a total of 128 students across six class periods. Out of these, 100 consented to participate in the research. In the post-survey, 97 participants reported their demographic information: 49 identified as girls, 46 as boys, one as non-binary, and one preferred not to disclose. The racial/ethnic distribution was as follows: 38 Asian, 34 White, 20 Black/African American, 6 Hispanic/Latinx, 3 Native American, 5 self-described, and 3 preferred not to disclose[1]. The average age was 11.7 years (SD = 0.48). Of the participants, 87% identified as native English speakers, 54% reported speaking at least one heritage language at home (bilingual), and 46% were monolingual English speakers. Both parent consent and student assent were obtained before any data collection.

6.2.2 Experimental Conditions and Hypothesis

To investigate whether the entity feature impacts students' learning experiences, I conducted a between-subject experiment with two versions of AMBY: *AMBY with entity* and *AMBY without entity*. The student participants were assigned to either condition to use AMBY to create their conversational apps, based on the number of consented participants in each class sessions and class logistics. I hypothesized that students who have access to the entity feature in AMBY will show a **higher enjoyment in creating chatbots** (measured in post-survey). Furthermore, the chatbots they produce are expected to demonstrate **higher project quality**, assessed across four dimensions: project ideation, conversation design, AI development, and end-user satisfaction.

1 Participants could identify with more than one race/ethnicity.

6.2.3 Study Description

The study was conducted for ten total study days over four weeks during students' regular science class time. Same as the regular class period, the classroom activity lasted 50-60 minutes per day. Table 6-2 shows the daily study schedule and data collection for each day. At the beginning of the study, students were informed by the teacher that the chatbots they developed during the classroom study will be graded by their teacher as part of their grades for the class.

Based on the number of consenting participants from each class period and classroom logistics, students from the first three class sections were assigned to *AMBY without entity* condition, students from the last three sections were assigned to *AMBY with entity* condition. 47 students were assigned to *AMBY without entity* condition and 53 students were assigned to *AMBY with entity* condition. The teacher characterized the different class sections as having similar average student grades prior to the study.

For the *AMBY with entity* condition, all students from the class period were using AMBY with the entity feature available during their learning. These students were introduced to the concept of entity and have a hands-on practice session on Day 4, before their project development. To control for the interaction time on AMBY for the two conditions, the control group (*AMBY without entity*) engaged in a similar hands-on activity on day 4, where they were guided to add more intents to their existing personal chatbots.

To avoid disadvantaging students in the control group from learning the concepts of entity, students were sent a tutorial about using Dialogflow and entity after finishing their projects.

On days 1, 2, 3 and 4, the students learned the relevant concepts of AI and conversational AI. Day 4 also involved the introduction of the entity feature for the students in *AMBY with entity* condition. Day 5 was dedicated to a formative assessment using Kahoot (an interactive quiz game commonly used in K-12 classrooms) and brainstorm project ideas. Days 6 and 7 featured project development, where students worked in pairs to develop a chatbot relevant to science topics they had learned in class. On day 8, students engaged in round-robin peer testing, where they tested each other's projects, offered feedback, and refined their

40-minute period	**Daily Tasks**	**Data collection**
Day 1	Assent, Pre-survey, Introduction to AI & Chatbots, Log in AMBY, Play with sample agents	Pre-survey
Day 2	AMBY lesson: Intents and Special intents. Hands-on practice: Modify 'AboutMeBot' on AMBY	No collection
Day 3	AMBY lesson: Follow up intents, Hands-on practice	No collection
Day 4	AMBY lesson: Conversational Design Principles, (1) entity lesson, hands-on practice on entity or (2) hands-on practice on existing agent	No collection
Day 5	Kahoot, introduce design log, pair brainstorm project ideas	Kahoot, design log worksheet
Day 6 & 7	Pair programming: Project Development	Video/audio/screen, chatbot artifact, collaboration questionnaire
Day 8	Peer review round robin	No collection
Day 9	Project development, post-assessment, post-survey	Post-assessment, post-survey
Day 10	Interview about AMBY feature and AMBY project	Interview

[a] Tasks for the *AMBY with entity* condition and *AMBY without entity* condition

[b] One class period in the *AMBY with entity* condition was extended by an extra day due to the larger class size and additional time needed for class management. Consequently, the entity lesson and practice were postponed to day 5. All subsequent activities were also delayed by one day, although the content remained the same with that of other periods.

Table 6-2. Classroom study schedule (each day is approximately 40 minutes of content)

projects based on their peers' feedback. On Day 9, students engaged in a paper-and-pencil test to assess their knowledge gain in AI. They also completed the post-survey to reflect on the classroom activities. On Day 10, I selected 20 pairs of participants for interviews to gather in-depth feedback on the AMBY feature and their projects. To ensure the students were comfortable talking to the researchers during the interview, selection priority was given to those who had more personal interactions with the researchers (e.g., through asking questions during previous lessons, requesting for help with debugging). Additionally, participants who had used the entity feature were given preference for the interviews.

6.2.4 Data collection

The results presented in this chapter are based on the following data channels:

- **Pre-/Post-Questionnaires.** Both pre- and post-questionnaires (Appendix D) include the AI attitude items adopted from The Barriers and Supports to Implementing Computer Science (BASICS) questionnaire [97]. The constructs include ability beliefs, persistence, identity, and interest (administered in the post only). In addition to answering the AI attitude items in a 4-point Likert Scale, in the pre-questionnaire, students reported language background and prior experience in programming. In the post-questionnaire, students wrote reflections about their experience of the classroom activities and reported their demographic information.

- **Observational field notes.** The researchers in the classroom observed the environment and student conversations and feedbacks about the classroom activities.

- **Student-created chatbot artifact snapshots.** 51 student-created chatbot artifacts were collected for outcome evaluation. Most of these chatbots were developed by pairs of students, while a few were created by individual students without partners. The artifacts contains the student project source files, in which each source file contained the relevant metadata associated with a chatbot, such as the intents, training phrases, responses, and entities in a structured natural language format.

- **Worksheets, reflection notes**: As part of the AMBY activity, participants completed a Project Design Log (Appendix A) to demonstrate the purpose of their chatbots. During

the learning activities, students completed worksheets or were prompted to write reflection notes about the learning activities.

- **Post-assessment**: Students completed a paper-pencil-based post-assessment (Appendix E) to evaluate their learning based on the learning objectives (Table 6-1).

- **Focus group interview**: On the final day of the study, we invited 20 student pairs (totaling 40 participants) to participate in the focus group interviews. These interviews were conducted by three researchers simultaneously, each with one pair of students and lasted about 20 minutes. During the interview, we gathered information about their project experiences, suggestions for improving the design of AMBY, perceptions about the debugging and entity features. Additionally, we discussed their views on using large language models for project evaluation. The focus groups were audio-recorded and later transcribed by a third-party service. The transcripts were first segmented by topics, and we employed a thematic analysis approach, as outlined by Naeem et al. [90], to analyze the relevant topics. One primary coder initially initially coded the responses, and a second coder reviewed these codes and applied a secondary coding as needed. The two coders[2] then met to discuss their coding decisions and resolve any disagreements.

6.2.5 Chatbot Artifact Evaluation Process

The student projects were evaluated[3] across four dimensions: 1) project ideation; 2) conversational design; 3) AI development; 4) end-user satisfaction (EUS). For the first three dimensions, specific project aspects were rated on a scale of 1 to 4, where 1 indicated little to no evidence of approaching expectations, 2 indicated approaching expectations, 3 was meeting expectations, and 4 exceeded expectations. Table 6-3 details the criteria for a "meets expectations" rating (score = 3) in relation to specific project aspects. The full rubric is in Appendix C. The rubric was collaboratively developed and reviewed by seven members of the project team[4] with diverse backgrounds (cs education, AI, software development, middle

2 Special thanks to Shan Zhang for helping with qualitative coding.
3 Special thanks to Carly Solomon, Wesly Ménard, David Vallejo-Lozano and Madison Edwards for helping with artifact data annotation.
4 Special thanks to Christine Wise, Joanne Barrett, Yukyeong Song, Amit Kumar, John Hoang, Carly Solomon for helping with artifact rubric development.

school teaching, and evaluation). The average Cohen's weighted kappa across all rubric dimensions was 0.82, indicating almost perfect inter-rater reliability [86].

The fourth dimension, end-user satisfaction (EUS), was assessed through interactions mimicking an end-user's experience with the chatbot. This dimension was rated on a 5-point Likert scale with statements adapted from Walker et al. [139]: 1) The agent was easy to understand; 2) The agent understood what I said in this conversation; 3) In this conversation, it was easy to find the information I wanted; 4) I knew what I could say at each point of the dialogue; 5) The agent worked the way I expected; 6) I would like to talk to the agent again. To eliminate potential bias, the EUS dimension was independently evaluated by three external annotators who were experienced in building chatbots and teaching middle school students but not directly involved in the study. The final EUS score was the average score from these three annotators.

6.3 Data analysis and results

In this section, I present the results of the classroom study. I first report the findings on the impact of the entity feature, then I report the post-hoc findings about the classroom intervention.

6.3.1 Entity feature effectiveness

To test the hypothesis regarding the effectiveness of the entity feature, I conducted independent sample t-tests on students' self-reported enjoyment scores and the quality of their project scores of participants in the *AMBY without entity* and *AMBY with entity* conditions.

6.3.1.1 Impact on enjoyment

My first hypothesis was that "The entity feature will enhance students' enjoyment in creating chatbots." Students' enjoyment was indicated through self-report responses to the enjoyment items in the post-questionnaire: "Creating a chatbot is exciting" and "Creating a chatbot is enjoyable", both rated on a 4-point Likert Scale. For this construct, students in the *AMBY without entity* condition reported an average score of 3.41, with a standard deviation (SD) of 0.76; students in the *AMBY with entity* condition reported an average score of 3.44, with an SD of 0.57. There is no statistically significant difference on students' enjoyment in creating chatbots between the two conditions ($p = 0.837$, $t = -0.2$).

Dimensions	Project Aspects	Statement for Score of 3 (Meets Expectations)
Project Ideation	Demonstrating purpose	The student has a clear idea of what the bot will do and implements their idea clearly.
	Chatbot Personality design	The agent demonstrates a unique personality through at least two of linguistic and visual choices (avatar, voice, word choice) and demonstrates intentional thought to align with chatbot purpose.
Conversational Design	Overall Intents	Project intents align with its purpose. The project has a balanced overall structure of the intents, has reasonable variation. Some adjustments could be made for streamlined design.
	Main intents	The majority main intents (more than 60%) are mutually exclusive and sufficient in demonstrating the purpose.
	Follow up intents	The agent has multiple logical follow-up intents AND Each follow-up intent is related to its parent intent mostly logically. Most follow-up intents can be triggered properly based on the responses from their parent intents.
	Greet intent	The agent has at least one customized greet response demonstrating its purpose. May not set exact user expectations.
	Default fallback	The response is created by the learner and can redirect the users.
AI Development	Training phrases	Most training phrases are ample, cohesive, and varied within the intent.
	Responses	Most customized intents contain at least one response that is in proper length, logical, and mostly mimic natural conversation.

Table 6-3. Student chatbot project evaluation criteria for the first three dimensions

6.3.1.2 Impact on chatbot artifact quality

Next, I tested the second hypothesis: "The chatbot artifacts produced by students in the *AMBY with entity* condition will exhibit higher project quality," using a validated rubric to evaluate across four dimensions: project ideation, conversation design, AI development, and end-user satisfaction. Table 6-4 shows the descriptive statistics for these dimensions. My analysis involved a sample of 51 projects, with 24 projects created under the *AMBY without entity* version and 27 projects created under the *AMBY with entity* version. The results, presented as means and standard deviations for each group, indicated very similar performance across all project dimensions. Independent-sample t-tests also revealed no statistically significant differences in the measured dimensions of project quality between the

two conditions.

Notably, the average score for all 51 artifacts, regardless of entity conditions, in the project ideation, conversational design and AI development dimensions were all above a score of 3 (*"meets expectations"*), indicating students generally went above and beyond our expectations.

	All projects (n=51)		**Non-entity (n=24)**		**Entity (n=27)**		**P-value**
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	
Project Ideation	3.04	0.4	3.04	0.46	3.04	0.34	0.97
Conv Design	3.24	0.35	3.26	0.34	3.22	0.35	0.68
AI Development	3.16	0.25	3.19	0.29	3.13	0.22	0.42
EUS	3.45	0.81	3.56	0.72	3.36	0.88	0.38

Table 6-4. Comparison of chatbot scores by condition. The four project dimensions are: project ideation (scale 1-4), conversational (conv) design (scale 1-4), AI development (scale 1-4), End-user Satisfaction (EUS, scale 1-5). P values were obtained from independent-sample t-test between the non-entity and entity conditions.

To further explore the potential impact of entity usage, I analyzed the 27 projects created in the entity condition. I categorize these projects into two categories: projects that did not include any entities, and those that contained at least one entity (indicating that the students had attempted and invested time in using the entity feature). Table 6-5 compares the project outcomes of the two usage groups. Given the smaller sample size for each group (18 projects did not use entities and 9 projects used entities), I conducted the Mann-Whitney U tests to compare the differences between these two groups. Mann-Whitney U test is the non-parametric equivalent of independent-sample t-tests, which does not assume a normal distribution of the data [113]. The tests showed no statistically significant differences between the two groups. In fact, projects that incorporated entities into their chatbots scored slightly lower (qualitatively, not statistically) across all four dimensions than projects that did not use entities.

Entity Usage	Did not use (n=18)		Used (n=9)		P original	P adjusted
	Mean	SD	Mean	SD		
Project Ideation	3.11	0.32	2.89	0.33	0.22	0.35
Conv Design	3.25	0.39	3.15	0.27	0.31	0.35
AI Development	3.19	0.25	3.00	0	0.037	0.15
EUS	3.42	0.90	3.23	0.87	0.35	0.35

Table 6-5. Comparison of chatbot scores by the usage of the entity feature in the *entity* condition. P-values were derived from the Mann-Whitney U test comparing the two groups. I report both the initial P-values from individual comparisons, as well as the adjusted P-values using the Benjamini-Hochberg correction [125] to account for the effects of multiple comparisons.

6.3.1.3 Entity feature usage and perception

In this section, I analyze how students used the entity feature specifically, using the snapshots of their final projects. Of the 27 projects in the *AMBY with entity* condition, 18 (66.7%) projects did not contain an entity, while 9 (33.3%) contain at least one entity in the chatbot. Among these 9 chatbots with entities, only 3 chatbots integrated the created entities into the training phrases or responses of their intents. The other 6 chatbots either adopted their entities minimally or did not integrate them at all to the intents of their chatbot. Here, I highlight two chatbot examples that adopted entities in different ways.

6.3.1.3.1. Entity Example 1: *ExperimentBot*. The first chatbot example is *ExperimentBot*, which introduced users to different steps and fun facts about the scientific method, fun experiment ideas, and lab safety requirements. Figure 6-1 is the overview of the intent structure and the list of entities created for the chatbot. In this chatbot, the students created three entities ("yes," "no," and "help") that captures common user expressions of acceptance (e.g., "sure," "okay"), rejection (e.g., "no," "nope") and request for help (e.g., "I need help," "I'm not sure what to do"). The students applied these entities as abstractions for training phrases that carried specific sentiments and reused them across multiple intents (see Figure 6-2 for an example of usage within an intent). Both "yes" and "no" entities were reused four times, which reduced their repetitive work when handling similar follow-up requests across different intent topics. The chatbot received an average score of 3.22 (out of 4) for its

project ideation, conversational design and AI development evaluation dimensions, indicating that it exceeded expectations on average. It also received an average end-user satisfaction (EUS) score of 4.39 (out of 5), which is substantially higher than the class average EUS score of 3.45. This demonstrates how effective application of the entity feature helped maximize the reusability of the conversation elements and improved the overall quality of the chatbot.

During the focus group, the students who developed *ExperimentBot* noted that the entity feature was "*efficient*" and helped better manage their time and effort. As a result, they could devote more time to "*work on more important things instead of having to think of all these extra phrases and variations on the way.*"

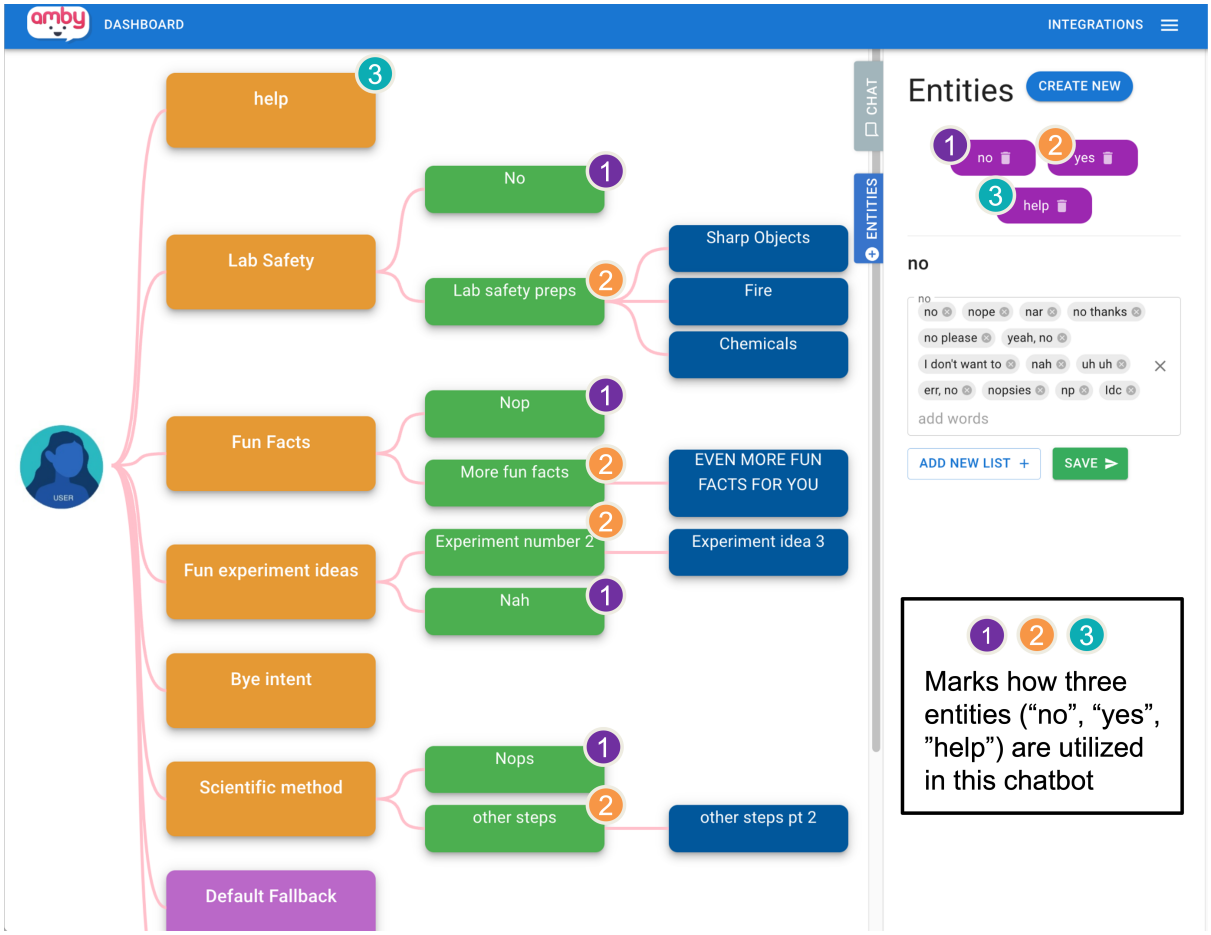


Figure 6-1. Chatbot example: *ExperimentBot*. This chatbot applies three entities ("yes", "no" and "help"). The colored circles marked as how entities are utilized across multiple intents.

6.3.1.3.2. Entity Example 2: *LivingThingsBot*.

The second chatbot example is *LivingThingsBot*, which described the seven characteristics and classifications of living things.

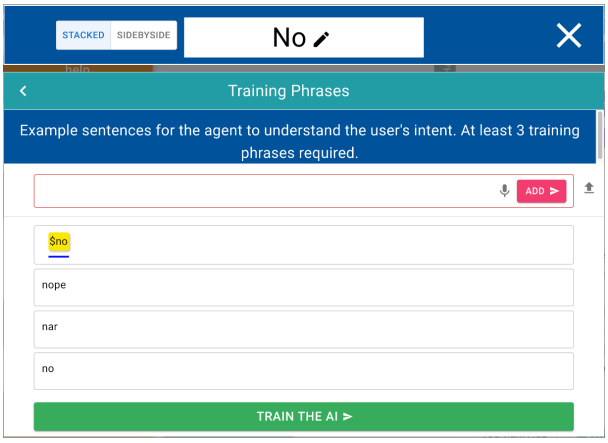


Figure 6-2. Screenshot of an example intent in *ExperimentBot*. In this "No" intent, the entity "no" is included as one training phrase but can represent multiple potential user expressions.

Figure 6-3 shows the intent structure and list of entities. The chatbot contained eight entities, each representing a class of animals or plants. For example, the "Mammals" entity included instances of mammals such as dog, cat, lion, and deer. The students incorporated all these entities into one intent "Specific Animal" to handle user information request for specific animals. Figure 6-4 shows how entities were utilized in both training phrases and responses within one intent, an example conversation is shown in Figure 6-5. Their usage case was novel: instead of creating multiple follow-up intents to branch out responses, the students placed all conditional responses into a single intent. This approach abstracted multiple intents with similar functions into one intent and made a complex chatbot easier to maintain.

However, the responses of this intent would need some refinement to interact with users smoothly. For example, instead of "`$Reptiles.original$ Alligators and Crocodiles, like other reptiles, all lay eggs,`" a better design would be "`$Reptiles.original$ ~~Alligators and Crocodiles,~~ like other reptiles, all lay eggs.`"

The average score for this chatbot was 2.89 (out of 4) across project ideation, conversational design, and AI development, which was slightly below expectations (cut-off point 3). The end-user satisfaction (EUS) score was 1.94 (out of 5), significantly lower than the class average of 3.45. Specifically, the chatbot lacked information to direct or guide users toward the correct intent and had no conversational hints to keep the conversation going. All

these fundamental elements of a conversation directly impacted project evaluation and user satisfaction. Despite their innovative use of the entity feature, students might have focused too much on using the feature and overlooked refining other important aspects of the chatbot.

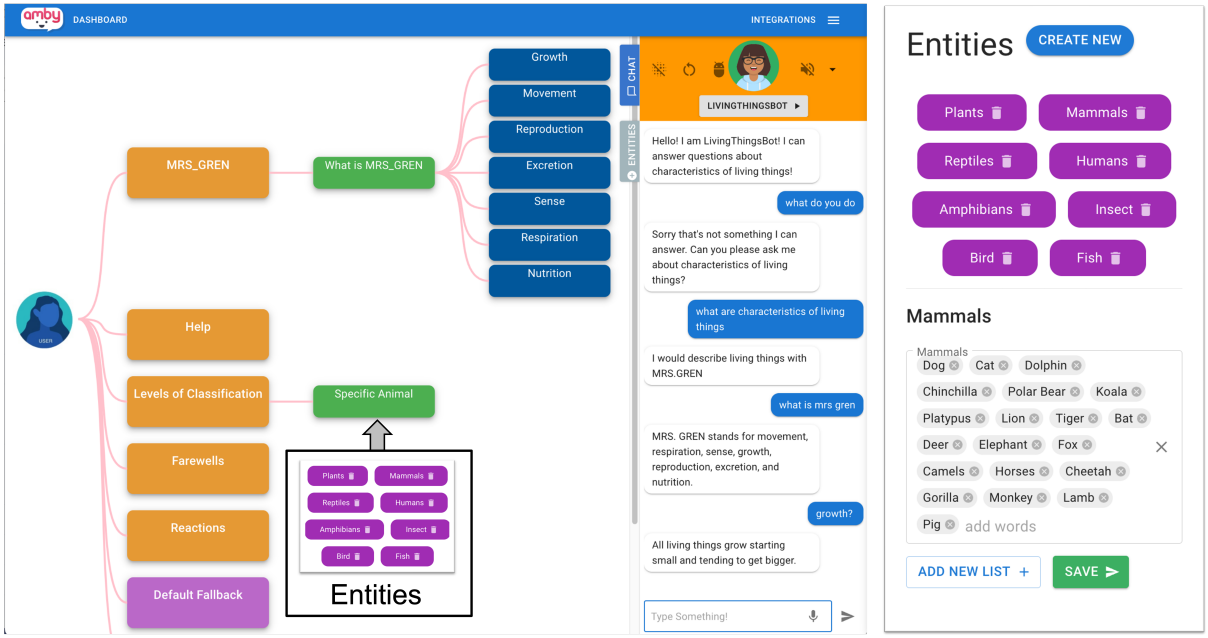


Figure 6-3. Chatbot example: *LivingThingsBot*. This chatbot applied multiple entities about different species, such as plants, mammals, and insects. All entities are utilized within one intent "Specific Animal".

6.3.1.4 Entity feature perception

Usefulness. During the focus group, the majority of students were able to articulate the concept of an entity and generally perceived it as useful. They acknowledged the that it would help save time and be efficient, flexible to be used across multiple intents, and produce more personalized conversation. Many considered it a "plus" feature, noting that they can still complete a fully functional chatbot without entities. Among the 12 student pairs (24 students) we interviewed within the entity condition, 7 reported they did not use entity, 2 reported they attempted but did not sufficiently use it, 3 reported they applied it successfully.

Challenges. The primary reason students did not use entities was because they felt their project topics did not require them. One student noted, "*I didn't feel like someone would be like, 'Yeah, the biosphere is so cool' because we already added a conversational intent.*" Another student added, "*Since we were only needing four constellations, it wasn't broad enough for entities.*" When being asked to provide potential topics that would be more

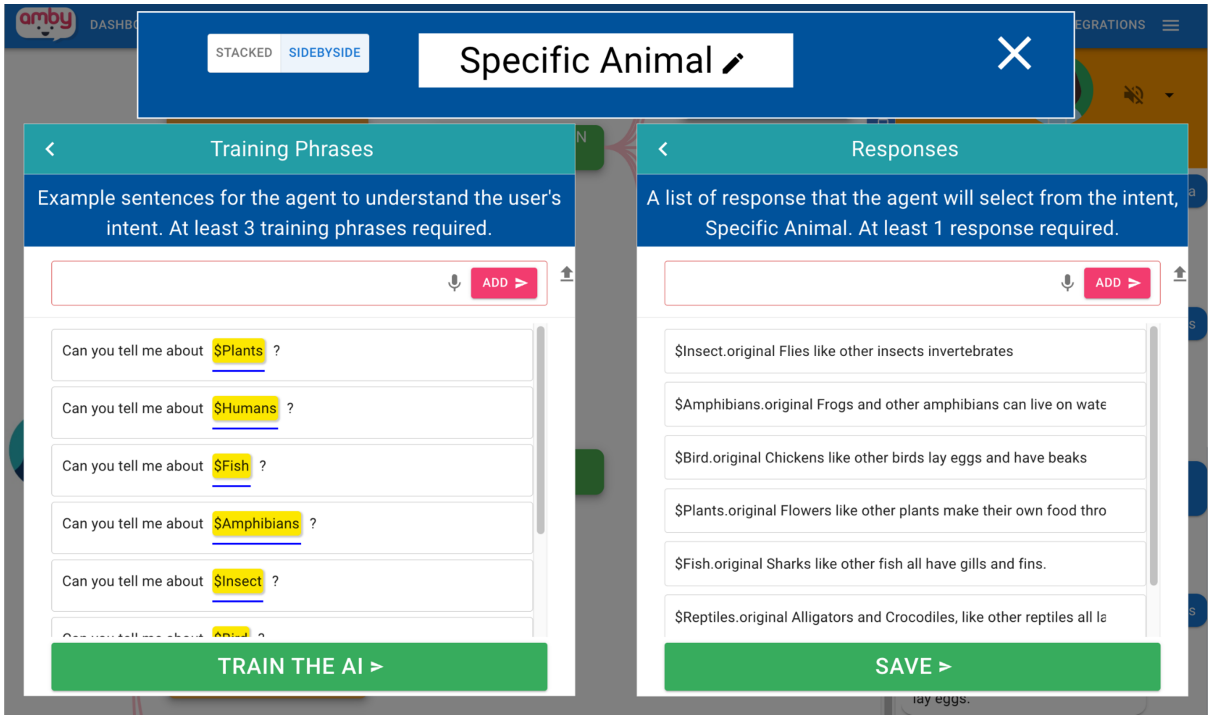


Figure 6-4. Screenshot of "Specific Animal" intent within in *LivingThingsBot*. Entities are used in both training phrases and responses.

relevant, students suggested topics such as food, weather, water cycle, and cells. While the benefit of entities may vary depending on the project topic and design, students seemed not to fully recognize the potential advantages of entities. Their comments reflect a misunderstanding of how entities can structure data and potentially enhance conversational flow. This could mean that they may not have fully grasp how entities can be effectively used regardless of the project topic.

Another reason students struggled with using entities was due to their perceived complexity and unclear functionality. One student mentioned, "*I don't get how to use entities. Sometimes when I click the dollar sign it immediately goes to the name of my* `entity.original`*, and I don't know how to change that.*" Another pair of students overestimated the scope and functionality of entities: "*We're going to use major cities in Florida for the weather, but that would have been too complicated (...) It wouldn't be able to update itself to the weather.*"

6.3.2 Post-hoc analysis on classroom activities

In addition to investigating the impact of the entity feature, I aggregated the data from both conditions and conducted a post-hoc analysis regarding the outcomes of the classroom

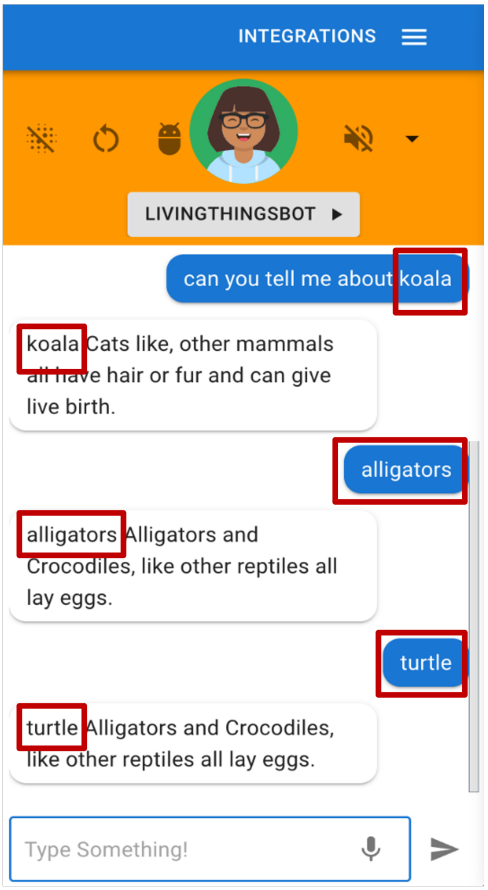


Figure 6-5. An example dialogue with the chatbot. In this sample dialogue, words in square boxes such as "koala," "alligators" and "turtle" from the user utterances are extracted as entities (i.e., "Mammals" and "Reptiles"), the specific entities then conditionally trigger customized responses. The chatbot can generate personalized replies using a predefined template response.

intervention. This aggregation was well-supported given that there were no extensive differences between the two conditions, as described above.

I examined how the integration of conversational AI into middle school curricula fosters students' learning about AI, as well as their attitudes and identities towards AI. This was assessed by comparing pre- and post-questionnaire results and the post-assessment outcomes. Given that all participants engaged in learning the core conversational AI learning modules, I did not expect significant differences between the two groups[5].

6.3.2.1 Attitudes toward AI

In the pre- and post-questionnaires, the AI attitude items were measured on a 4-point Likert scale, including three constructs: *ability beliefs, identity, and persistence*, adapted from

5 For completeness of the analysis, the outcomes between the two conditions were compared using individual sample t-test. The results indicated no significant differences between the two conditions.

BASICS-SQ questionnaire [97]. The *ability beliefs* construct assesses students' perceptions of ability to understand AI, with items such as: "I am confident that I can understand AI" and "I can figure out how to solve hard AI problems if I try." The *identity* construct asks students whether they see themselves having options in AI careers, with items such as: "If I chose to, I could have a job that uses AI. " The *persistence* construct examines the actions students might take in the near future related to AI learning, with prompts such as "I would like to learn more about AI in the future" and "I would like to join an AI club. " To investigate students' attitude change after the classroom intervention, I conduct a paired-samples t-test comparing the composite scores from each construct in the pre and post responses. A total of 92 students completed the pre-questionnaire, 97 students completed the post questionnaire, and 90 students provided both pre and post.

Table 6-6 shows a significant increase in students' *ability beliefs* from a mean score of 2.76 to 3.18 ($p < 0.0001$) and a decrease in *persistence* from a mean score of 2.89 to 2.69 ($p < 0.0001$), while identity construct did not show a significant change ($p = 0.203$).

6.3.2.2 Situational Interest

The interest outcomes, based on Hidi and Renninger [51]'s interest development model, include triggered and maintained situational interest. Triggered interest had an average score of 3.26 with a standard deviation (SD) of 0.54 and included three sub-constructs: Exploration Intention, with statements such as "I want to learn more about how conversational AI apps (like Siri, Alexa, Google Home) work"; Attention Demand, with statements such as "Time in this class passed quickly while working with AMBY"; and Instant Enjoyment, with statements such as "Creating a chatbot was enjoyable." Maintained interest had an average score of 3.07 with an SD of 0.7, comprising two sub-constructs: Personal Meaningfulness, with statements like "Making a chatbot is meaningful to me" and "I am proud of the chatbot I created," and Sharing, which includes statements such as "I would like to show my chatbot to my friends" and "AMBY is something I would like to use at home." The positive sentiment showed on Table 6-6 (scores greater than 3, falling between "agree' and "strongly agree') suggests that students generally felt engaged and valued their learning experience.

	Pre		Post		Difference (post-pre)	p value	Effect size
	Mean	SD	Mean	SD			
Ability Beliefs	2.76	0.60	3.18	0.53	0.43	< 0.0001	0.71
Identity	2.69	0.59	2.60	0.78	-0.09	0.203	0.14
Persistence	2.89	0.55	2.69	0.68	-0.20	< 0.0001	0.43
Triggered Interest			3.26	0.54	–	–	–
Maintained Interest			3.07	0.70	–	–	–

Table 6-6. Participants' (n = 90) attitude and interest from pre- and post-questionnaire. Items were measured in 4-point Likert scale (1-4). SD: Standard Deviation. P values were obtained from paired-sample t-test between pre and post. Effect sizes were calculated using Cohen's D.

6.3.2.3 AI knowledge assessment

Students' conversational AI knowledge was assessed through a paper-pencil post-assessment. The assessment was collaboratively developed by two researchers, one specialized in CS/AI (myself) and one specialized in education evaluation and K-12 classrooms[6]. The questions were adopted from a validated cognitive interview protocol originally developed by four members of our team, and was implemented as a form of post-assessment to supplement paper-based test over two years of summer camps. This paper-pencil assessment comprised 15 questions: 14 were multiple-choice, and one was open-ended. Each question correlated with a specific learning objective, as outlined in Table 6-1. Of these, 13 questions targeted to measure students' understanding of *conversational AI concepts* and 2 questions for specific *entity concepts*[7]. Table 6-7 shows the correct response rates from students.

We did not conducted a pre-assessment. Because there was no comparable AI curriculum at the participants' school, the assessment items were highly contextualized in both the our curriculum and the learning tool, AMBY. It is reasonable to presume that the participants did not have prior knowledge in this area. Reading a difficult material in the pre-test could potentially harm the learning experience by causing frustration [80] and

6 Special thanks to Christine Wise for helping with AI knowledge assessment development.

7 Although half of the students were in the "non-entity" condition, their post-assessment still included questions about entity concepts to maintain consistency in outcome measurement.

Student group	Overall AI knowledge (15)		Conversational AI knowledge (13)		Entity knowledge (2)	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Non-entity (n=46)	0.91	0.07	0.96	0.06	0.59	0.35
Entity (n=52)	0.89	0.07	0.95	0.07	0.54	0.35
All students (n=98)	0.90	0.07	0.95	0.06	0.56	0.35

Table 6-7. Post-assessment scores. (15), (13) and (2) indicate the number of questions the scores were calculated from.

diminishing the students' interest in AI, as they have not been exposed to such material before the intervention.

The results from Table 6-7 show a substantial mastery of the learning concepts. The average correct percentage across all students for their overall learning was 90%, and for the conversational AI knowledge, it was even higher at 95%. This indicates that our classroom intervention was generally successful in achieving the learning objectives, with the majority of students mastering most concepts.

However, the average score for the two entity questions was only 56%, indicating some misunderstanding about the entity concept. This lower performance could have been due to several factors. One possible reason might have been that the distractors in these questions were challenging, which could have confused the students. Additionally, the limited time allocated for this specific part of the curriculum may not have been sufficient for students to effectively internalize and apply the entity concepts to new contexts beyond the examples discussed in class.

There was no statistically significant difference in students' understanding of the learning concepts between the non-entity and entity groups.

6.3.2.4 Student perceived impact on science learning

When asked whether the classroom intervention helped students understand science concepts learned from class in the post-study questionnaire (i.e., "*Did the conversational AI lessons and activities help you understand science concepts you learn from class? If so, how?*"), there was a split opinion among the participants. Approximately 52% (50 out of 97) of students responded positively, indicating the benefits such as having to articulate concepts

clearly, engaging more thoroughly with the material, refreshing their memory, and learning additional details to expand what was taught in class. Some participants noted:

> "*Yes!!! I had to think about how to explain something that we learned and think about different questions. And you have to understand something to explain it through AI.*"

> "*Yes me and my partner chose Living things for our chatbot and it helped us further understand science concepts that we learned as it made us research more about Mrs. Gren and other characteristics of living things.*"

A few students also found value in reviewing and interacting with their peers' projects:

> "*We did tornadoes but some chatbots did help us learn about the scientific method steps.*"

Conversely, 48% (46 out of 97) indicated that the AI lessons did not enhance their comprehension of science concepts taught in class. The primary reason was that the content integrated into their chatbots was already familiar: "*The science concepts that we made were put in by us, so we had to know the concepts beforehand. Hence, it did not help us learn new concepts.*" Additionally, many students viewed the AI activities as distinct from their standard curriculum, describing "*I think it was more a lesson on its own.*" Moreover, for those whose chatbot topics were not yet covered in their syllabus, such as dinosaurs, astronomy, and plants, the benefits were indirect. Instead of directly reinforcing class-taught concepts, these topics provided a broader scope of knowledge that could be useful later, as one student noted: "*Not really, we haven't really learned about fungi. But this gave me hope for ideas in the future. And I should get an A when we do learn about fungi.*"

6.4 Discussion and Implications

In this study, I deployed AMBY 2.0 interface in a formal classroom setting. I primarily examined the impact of the entity feature on students' enjoyment and their project quality. The statistical results did not find support for the hypothesis that the entity feature significantly influenced students' enjoyment levels, nor the measured dimensions of project outcome. One

possible reason for the enjoyment is that students in both groups reported a high enjoyment score (3.4 out of 4), indicating that interacting with AMBY and creating chatbots was so novel that it brought stronger impact on students' overall enjoyment, which could have overshadowed any benefits from the entity feature. Regarding the project outcomes, the limited influence can be attributed to a low adoption and usage of this feature. Among the 27 student groups in the *AMBY with entity* condition, only 9 groups attempted to use this feature, and only three groups applied it as a major component of their chatbots. While the majority of students understood the concept of entity and generally perceived it as useful, many considered it as an optional "plus" function. Because we did not force students to use this "advanced" feature nor the teacher were grading projects based on its usage, students were less motivated to explore the feature within a limited class time. Although effective use of the entity feature could potentially improve their efficiency and end-user interaction, other aspects, such as creating more follow-up intents and adding conversational markers, seemed to be more directly relevant to their final grades.

Speaking more broadly, abstraction is a core concept in CS and AI. According to AI Big Idea #2: Representation and Reasoning, children should be exposed to the representations of different data types in different AI applications [1]. Entity, as one form of data abstraction and an important concept in NLP, provides a novel approach to further enhance students' abstraction skills within conversational AI. Future research should explore diverse data representation methods in introductory AI to introduce children to the concept of abstraction whenever possible.

Teaching abstraction to children can be challenging, especially in a formal classroom environment. Our study identified several challenges related to learning about entities, which include students perceiving them as less relevant to their project topics and felt the feature complex and unnecessary. Many studies have reported similar issues regarding students' understanding and application of abstraction in different CS contexts [121, 87, 12, 95]. Armoni [12] discussed how high school and undergraduate students face challenges in abstracting problems into algorithms and often undervalue the importance of algorithms. Or-Bach and Lavy [95] observed that students in object-oriented programming often fail to

leverage the full potential of abstract classes; instead of reusing code, they tend to avoid modularization and end up duplicating the code. It is important to develop more effective strategies and tools for teaching children about this skill and to offer contextual and personalized support to learners.

Regarding the classroom study outcomes, the increase in students' ability beliefs suggested that the classroom intervention successfully enhanced students' confidence in their abilities related to AI. This likely resulted from the engaging AMBY project development experience, which made them better understand the AI concepts and made AI seem less intimidating. The decrease in persistence might suggest that the initial excitement about learning AI wore off after the intervention. To take a closer look at the changes of the individual items, I noted that these two statements, "I would like to learn more about AI in the future" (Pre: 3.46 ; Post: 3.15) and "I would like to take a class in AI" (Pre: 3.01; Post: 2.64) had dropped most substantially. It is not surprising to see that students were less likely to take further actions after gaining AI knowledge and experience during our classroom activities. There was no significant difference in the identity construct. The findings about the ability beliefs and identity in this classroom study were consistent with our prior summer camp outcomes [120].

The findings of the classroom intervention reported by students suggested a strong alignment with theories of constructionism and authenticity [119, 98]. Students highlighted the customization and creativity involved in building their conversational agents and expressing a sense of ownership and personalization. One student noted that "*It was fun we could make the AI's 'personality'*." Participants expressed a clear understanding of the real-world relevance of the chatbot development task, such as "*It was fun to make my own AI which made me think of all the hard work people tools to make other AI's such as google or siri.*" From another student: "*I think creating the chatbot was fun and enjoyable to do with a partner, and the lessons really helped me understand AI.*" suggesting that the learning experience fostered teamwork and social interaction. Overall, the alignment with the educational theories of constructionism and authenticity likely contributed to the engagement and effectiveness of the intervention.

From a human-centered computing standpoint, the classroom intervention could be further strengthened by incorporating built-in support features within the interface. During the interview, many students suggested to add tutorials through the use of the AMBY platform and its functionalities. One student noted "*There could be a chatbot about AMBY.*" This is especially crucial in formal classrooms where timely individualized support may not always be feasible. Scaffolding the presentation of key concepts, especially more complex ones such as entity, would also be beneficial. Additionally, integrating automated assessment and feedback mechanisms could help students track their progress, identify areas for improvement, and receive timely feedback throughout their learning. Researchers in AI in education and educational data mining community have shown promising results to automatically assess student progress in computational artifacts [129] and short answers [37], and ways to trigger concept scaffolding [7] and program repair [66]. With the rapid development of large language models (LLMs) and their use in education across many disciplines [37, 88], future research could explore LLM-based approaches to support AI learning systems at scale. This not only enhances the efficiency of the learning process but also democratizes access to high-quality education, making AI education more inclusive and accessible to a broader range of learners.

6.5 Conclusion

In this chapter, I present the deployment and findings of the AMBY 2.0 classroom study, aimed at evaluating the impact of the "entity" feature–an instance of data abstraction–on students' enjoyment and project outcomes. The study involved 100 children using the updated AMBY 2.0 interface in a between-subject experiment with two conditions: *AMBY with entity* and *AMBY without entity*. Contrary to my expectations, the results did not find significant differences in the hypothesized outcomes between the two conditions. Additionally, I provided qualitative insights into specific places where students faced challenges or held misconceptions.

This study illustrates an innovative approach to teaching data abstraction to children in AI education context. The findings suggest that the concept of abstraction was challenging for students to fully leverage, where built-in support and automated approaches could help facilitate learning. Future research should develop effective design strategies to support this

type of learning in young students.

Furthermore, I examined how the integration of conversational AI into middle school core subjects such as science shapes students' attitudes towards AI and impacts their interest and knowledge. The findings shows a significant increase in students' ability beliefs, though it decreased their intention to persist in learning about AI. Students were highly interested, and their post-assessment results demonstrated substantial understanding of the learning concepts.

This classroom integration offers valuable opportunities for students to learn the interdisciplinary nature of AI and its applications across various fields of study and aspects of life [72]. This study contributes to AI education in formal classrooms and suggests pathways for further research in making AI learning more effective and engaging for young learners.

CHAPTER 7
CONCLUSION AND FUTURE WORK

This dissertation has addressed a crucial gap in human-computer interaction and computing education research by exploring how we can provide engaging and authentic AI learning experiences for children. Through a multi-year study around a novel learning tool, AMBY, my research examined four study phases: AMBY design (Chapter 3), summer camp deployment (Chapter 4), AMBY refinement (Chapter 5), and the final classroom study (Chapter 6). The findings significantly advance our understanding of how to empower children with AI learning through creating their personally relevant conversational agents in both informal and formal learning environments.

7.1 Summary of Contributions

Design Contributions. Prior to this dissertation, the ubiquity of AI and the importance and urgency of AI education for children was broadly recognized [130]. It is also well-established by constructionism theories and authenticity literature that building personally relevant artifacts can be effective in fostering learning [98, 58, 119]. Despite the prevalence of conversational agents such as Siri and ChatGPT, there were a limited set of tools designed to help children create conversational agents that were both developmentally appropriate and educational [40]. This dissertation made significant design contributions by applying child-centered design principles, which were informed by prior literature and multiple studies I conducted with children. These efforts led to a set of design recommendations for child-centered AI-authoring tools that enhance AI education for children. The design recommendations suggest that child-centered AI-creation interfaces should be easy to engage with even for children without programming experiences, offer a high ceiling to foster learning complex concepts such as abstraction, be transparent in the AI training process, offer adaptive support and personalized feedback, and support children to demonstrate their knowledge and skills through the artifacts they create.

Educational Contributions. In computing education, the importance of teaching abstraction skills to children has been widely recognized [87, 12]. This dissertation introduces an innovative approach to teaching data abstraction within the context of AI education. AMBY supports children to apply "entity" to simplify the creation of repetitive training data

and produce personalized responses to the end-user. This allows students to enhance the dialogue design for their artifacts. My observations from student interactions with this feature indicate that while the feature was not universally adopted, those who did utilize it were able to integrate it into their project designs in effective and creative ways. These findings confirm the importance and challenges of teaching abstraction to young students. The results suggest the need for designing adaptive support and automated approaches to facilitate this type of learning among young learners.

There is a significant need to integrate AI into K-12 classrooms to ensure consistent and quality AI education for all learners. However, many schools and teachers lack the resources and learning tools to support CS and AI learning for their students [23, 93]. Bringing AMBY and the conversational AI curriculum into core school subjects can bridge this critical gap by providing an accessible platform for students to learn AI concepts in a relevant and engaging manner. This dissertation demonstrates how the integration of AI into middle school science classrooms can improve attitudes, benefits interest formation and students' learning experiences, which contributes to the state of knowledge in computing education research.

7.2 Future work

This dissertation opens several research directions. I have investigated the use of "entities" in children's conversational agent design, which is similar to the concept of "variables" in programming, as a novel way to introduce abstraction and core natural language processing concepts. Future research could explore more diverse methods of teaching abstraction in the context of AI, such as in the tasks of image recognition and generative AI. This could further enrich students' understanding and application of computing concepts.

Another direction for future research is developing adaptive and personalized support for teaching these complex concepts in the classroom setting. In my study, one reason the entity feature was not widely adopted by students can be the limited personalized support available to guide problem-solving and resolve confusion, which is common reported in classroom settings. Future studies could use large language models (LLMs) to monitor student learning progress and generate automated feedback. However, AI-based support for children should be approached cautiously, especially children tend to perceive smart applications

differently than adults [32]. Design principles should aim to maintain safe and positive learning experiences and to mitigate potential biases and misconceptions for children [30]. Examining human-in-the-loop approaches could give teachers and learners more autonomy and enhance the quality of feedback [36].

Scaling up the AMBY program and its curriculum is another important area for future work. This scale-up should aim to benefit a broad set of learners and include teacher professional development programs. These programs would equip middle school teachers to lead the activities independently without needing intervention from researchers. Moreover, integrating conversational AI into other subjects, such as social science and language studies, could allow students to learn about the applications of AI in different contexts.

APPENDIX A
DESIGN LOG DOCUMENT TEMPLATE

Next page is the design log that learners used to document the process of creating conversational agents.

PROJECT DESIGN LOG

Enter the Name of your App Here!

Student Name

June 2022
Camp Dialogs

List of Sample Project Scopes	Goals
- Reminders/ Task oriented apps (e.g. remind me to do my homework) - Sports (e.g. sports in the olympics, what the record is, what my favorite player on the team, stats on a player) - Educational (e.g. accessing learning resources) - Gaming(e.g. tips, achievement tracker - Recipes(breakfast, lunch, dinner) - Motivational - Entertainment (e.g. movie recs, movie review) - Shopping Assistant - Mental Health	- Helping themselves - Helping family member

Empathy

Step 1: Understanding the people that will be using your app

Who will you be trying to help?	
What do you think they will need?	

Define the Problem

Step 2: Defining the challenges from your point-of-view

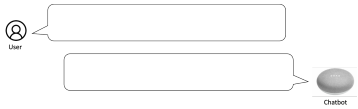
What is the problem you are trying to solve?	
How do you think you can solve this problem?	
Who will use this app?	
What will this app do?	

Ideate

Step 3: Brainstorming ideas and create solutions for your users

What are your ideas to solve this problem?	
Which idea is the most original?	
Which idea do you think is the easiest or most complex?	
What makes it easier or harder?	

Sample dialogue of your agent (write down on the paper sheet)



Prototype

Step 4: Drafting elements of the agent

What is your agent's name?	
What type of intents will your agent have (*Welcome* and *fallback* intents are provided for you)	

Test

Step 5: Testing your prototype and getting feedback

Follow the instructions provided by the camp counselors to set up your Google Home device for testing:

- Test the google assistant/ google home device and get feedback

Answer the following questions:

What worked well with your app?	
What didn't work well with your app?	
What can you change to make it better?	
What other ways might your user use your app?	

Modify

Step 6: Improving your prototype

What can you do to fix what didn't work well with your app?	
How can you make your app better?	

Share

Step 7: Showing your app

How will you show others your app?	

- Design a Logo or Icon that will represent your project:

APPENDIX B
LIST OF CONVERSATIONAL AGENTS THAT LEARNERS CREATED USING AMBY IN SUMMER 2022

Table B-1. Conversational agents that learners created using AMBY in Summer 2022. Descriptions given were written by the learners as they completed a design document for the project. The themes were summarized by myself. Note: Some learners named their agents after themselves; to protect their privacy, these are given as [redacted].

Theme	**Chatbot Name**	**Description**
Mental health	goldiethestressbot	Have a bot to talk about your feeling.
	MentalHealthBot	Provide support and answers to people that struggle with mental health problems.
	CalmBot	Give meditation advice, recommend calming things.
	ReachOutAnd-GrabaHand	A therapy bot that helps about marriage issues and emotions.
	diamond	Help people feel better in life and don't go through stress.
Game	Gaminglogicbot	Give introduction to three games, Fortnite, Roblox, and 2K.
	teacherbot	Teach my parents about the game Madden.
	BlahBot	Inform people about the video games.
	Rox-bot	Tell info about Roblox (and possibly Roblox games).
	Gamebot	Help friends with video game levels.
	Gamebot	Give tips to get past a certain part of the game (Animal Crossing).
	HorizonBot	Help with Animal Crossing New Horizons.
	FortniteBot	Help people get used to the game Fortnite.
Music/movie	boy_bot	Play music.
	JokerTheMusician	Tell people jokes and let them listen to music depending on their mood.
	Musicbot	Give people music recommendations.
	ezmae	Recommend music to people based on the genre they like.
	MusicBot	Recommendations of what music to play.
	Angelbot	Recommend interesting music and tell you facts about singers.
	Esmie	Provide good movies to watch.
	horrorbot	Recommend horror movies.
Personal/joke	hal-9000	Simply be funny. Tell jokes, play simple games, recommend music, and be funny.
	tmx-10000	Be funny. Tell joke, music, food, and stuff about pets.
	jackthejoker	Crack jokes back and forth.
	[redacted]	Tell you jokes and little things about me.

Continued on the next page

Table B-1 Conversational agents that learners created using AMBY (continued)

Theme	Chatbot Name	Description
	PinkusBot	Give song recommendations, giving advice on being happy and making jokes.
Task-oriented	MotiveBot	Help keep my grandad entertained and motivated.
	Home_Gurl	Help the teachers to know about dance.
	AngelGirl	Help with cooking and cleaning.
	Petbot	Reptile store, help with information buying reptiles, arachnids, and prey.
	AssistaBOT	Help me with homework or waking up early.
Recommendations	ShopBot	Suggest the best brands for clothes, shoes, accessories, etc.
	FashionBOT<3	Help people who need fashion advice.
	Gabby	Recommend gifts you can give to certain people of all ages and basic personalities.
	Artist_Helper	Help bored artists figure out what to draw and which styles to draw them in.
	ideabot	Creates ideas for people who are bored.
	FoodBot	Recommend restaurants and grocery stores.
	RecBott	Recommend books of different genres with marginalized people as main characters and properly portrayed.
Sports	Boxingcoach	Help people learn how to box and the rules.
	[redacted]	Tell people the key elements on playing dodgeball.
	BASKETBALL-BOT	Tell about my favorite basketball team, players, and skills.
	Sport	Tell the user about baseball.
	BasketballBob	Give information about basketball.
	BasketBallBen	A cool and fun way to learn about tips, history, and facts about basketball.
	Theyenvy_Nya	Give tips and information about volleyball.
	baldy	Teach about football.
	FootballBot	Tell you facts about football.
	Diamond	Teach about basketball tips and provide information about Steph Curry.
	KingBot	Teach people about LeBron James.
Educational	jerryberry	Teach people with black history, provide information about black influencers.
	OlympicBot	Inform the user about the Summer Olympics.
	ZooBot	Fun and interesting facts about animals.
	VRbot	Explain how VR works, what you can play, and some tips.
	Twinnem	Tell you interesting facts about Fraternal twins.
	Mathbot	Help people understand how to solve math problems.

Continued on the next page

Table B-1 Conversational agents that learners created using AMBY (continued)

Theme	Chatbot Name	Description
	botbot	Quiz on specific math topics.
	Cookie_Cutter	Tell recipes about cookies.
	DanceBot	Tell people about dance tips.

APPENDIX C
AMBY STUDENT PROJECT EVALUATION RUBRIC

Instruction on how to evaluate different dimensions:

1. **Project ideation:** the expert evaluators go through the chatbot content in AMBY (development panel, left side), in combination of looking at the design document from the individual/group, to understand the purpose of the chatbot and target users.

2. **Conversational design:** the expert evaluators go through the chatbot content (intents, training phrases, responses) in AMBY (development panel, left side).

3. **AI development:** same as "conversational design".

4. **End-User Satisfaction:** the expert evaluators test the chatbot as an end user without necessarily knowing/understanding the inner workings of the chatbots.

Table C-1 shows the statement for the end-user satisfaction dimention. Each item, adapted from Walker et al. [139] is rated based on 5 point likert-scale: 1 - Strongly Disagree, 2 - Disagree, 3 - Neither agree nor disagree, 4 - Agree, 5 - Strongly agree.

User Satisfaction Statement	**Aspects of User Perception**
The agent was easy to understand.	NLG Performance
The agent understood what I said in this conversation.	NLU Performance
In this conversation, it was easy to find the information I wanted.	Task Ease
I knew what I could say at each point of the dialogue.	User Expertise
The agent worked the way I expected.	Expected Behavior
I would like to talk to the agent again.	Future Use

Table C-1. End-User Satisfaction Dimension Statement

Table C-2. AMBY Student Project Evaluation Rubric for Project Ideation, Conversational Design, and AI Development Dimensions.

Dimensions	**Project aspects**	**1. Little to no evidence of approaching expectations**	**2. Approaching Expectations**	**3. Meets Expectations**	**4. Exceeds Expectations**
Project Ideation	Demonstrating purpose	The purpose of the design is vague / unclear OR The implementation has no clear purpose (the system is random)	The purpose is broad, not fully clear. OR The purpose does not meet the needs of their target audience OR the system implementation doesn't fit the purpose written.	The student has a clear idea of what the bot will do and implements their idea clearly.	The purpose is well-thought out, demonstrating the social connectivity by stating the chatbot is to help a specific group or community.
	Chatbot Personality design	There is no intentional linguistic or visual choices to align with the chatbot's purpose	The agent demonstrates at least one visual and linguistic choices including the following components (avatar, voice, word choice) but not all OR does not fully align with chatbot's purpose	The agent demonstrates a unique personality through at least two of linguistic and visual choices (avatar, voice, word choice) and demonstrates intentional thought to align with chatbot purpose	The agent demonstrates a unique personality through all of linguistic and visual choices (avatar, voice, word choice) And using the unique language consistently throughout and all visual and linguistic choices

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Table C-2 – continued from previous page

Dimensions	Project aspects	1. Little to no evidence of approaching expectations	2. Approaching Expectations	3. Meets Expectations	4. Exceeds Expectations
Conversational design	Overall Intents (mainly look at the conversation tree, not the testing result)	No progression of the conversation. OR Does not demonstrate the logical conversation patterns (the followup is completely disconnected from the main intent)	The dialogue tree has "gaps" (e.g., main intent only has one followup, or no followups)	Project intents align with its purpose. The project has a balanced overall structure of the intents, has reasonable variation (reasonable means an appropriate ratio and distribution for the main and follow-up intents)	The follow-up intents are well-developed. The overall flow of the dialogue tree is logical and creative
	Main intents	No customized main intents provided OR The customized intents are unrelated to the project purpose	The main intents are not mutually exclusive (some intents could be collapsed) and/or The intents are not comprehensive (not aligned with the project purpose, or lacking important information)	The majority intents (more than 60%) are mutually exclusive and comprehensive in demonstrating the purpose, some adjustments could be made for streamlined design	All intents are mutually exclusive and comprehensive of purpose, no design changes are needed

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Table C-2 – continued from previous page

Dimensions	Project aspects	1. Little to no evidence of approaching expectations	2. Approaching Expectations	3. Meets Expectations	4. Exceeds Expectations
	Follow up intents	No follow-up intent is provided	The agent has at least one follow-up intent OR most of the follow-up intents do not logically match with its parent intent (or the response cannot trigger the follow-up intent properly) OR most follow-ups are unnecessary or repeated	The agent has multiple logical follow-up intents. AND Each follow-up intent is related to its parent intent mostly logically	All of the follow-up intents are not only logically related to main intent and numerous, they are mutually exclusive
	Greet intent	No customized greet response is provided	The agent has at least one customized greet intent, however the purpose is not clear or actionable (e.g., “Hi, I’m Santa bot.”, “ask me anything you need!”)	The agent has at least one customized greet intent demonstrating its purpose (e.g., “You can ask me about XYZ”) May not set exact user expectations: (“Ask me for song recommendations”, “ask me about NBA tips”, “hey im blah bot do you need any assistance on video games?”)	The response(s) in the greet intent effectively greet the user (e.g., “hello”), introduce the chatbot (e.g., “I am MusicBot”), and demonstrate the purpose (“I can introduce XYZ”). AND Set exact user expectations (e.g., “I can talk about pop rock or hip hop music”) or clearly directs the user for next steps (e.g., “simply state ‘quiz me on math’”)

Continued on the next page

Table C-2 – continued from previous page

Dimensions	Project aspects	1. Little to no evidence of approaching expectations	2. Approaching Expectations	3. Meets Expectations	4. Exceeds Expectations
	Default fallback	No camper-created fallback response is given	The response is created by the camper, however it cannot not redirect the users (e.g., "I didn't get that. Try it again.")	The response is created by the camper and can redirect the users (e.g., "I didn't get that as I'm still learning. I'm more confident to talk about XYZ instead.")	The agent has multiple varied, customized and meaningful responses that can redirect the users
	Help intent	No help intent	The project has a "help" or equivalent intent but the training phrases is limited (less than 3) OR the response does not demonstrate the purpose clearly	The help intent can recognize common user expressions such as "I need help", "what can you do?" AND The project has a "help" or equivalent intent to help the user navigate the chatbot, within the intent, the response introduces the chatbot functions clearly.	The training phrases for the help intent are varied and numerous AND/OR The response allow the users to take actions (e.g., "I can do XYZ, what would you like to start with?") AND/OR Has multiple, varied, meaningful responses

Continued on the next page

Table C-2 – continued from previous page

Dimensions	Project aspects	1. Little to no evidence of approaching expectations	2. Approaching Expectations	3. Meets Expectations	4. Exceeds Expectations
AI Development	Training phrases	The amount of training phrases is limited (less than system requirement) OR Most of training phrases are random in the customized intents	The amount of training phrases meet the system requirement, but the content does not show enough linguistic variations (syntactically and lexically) within the intent or topic variations across different intents	Most training phrases are ample, cohesive and varied within the intent; also differ from those in other intents. They present variations in either syntactic structure or lexicon choices	The project contains consistently more varied training phrases than what the system requires, which can capture some edge cases. Training phrases are given and they are unique in both lexical and syntactic structure
	Responses	The responses are random in most of the customized intents	Most Responses (60%+) are provided either too long or too short, or lack of information or contains grammatical errors that impede user's understanding If there are multiple responses, the content is not consistent enough to trigger similar user reactions Example: "Bad Romance by Lady Gaga" - not conversational	Most customized intents contain at least one response that is in proper length, logical, mostly free of grammatical errors, mostly mimic/display natural and conversational, may include some conversational markers.	Intents contain multiple logical, error-free responses OR The responses contain hints to keep the conversation going (e.g., "Alligators are dangerous animals… Now, do you want to learn about other animals?) OR Utilize the conversational markers throughout the customized intents when appropriate

APPENDIX D
PRE- AND POST-QUESTIONNAIRE FOR THE AMBY CLASSROOM STUDY

Pre-survey

1. What is your first name?

2. What is your last name?

3. **Ability Beliefs**

   Prompt: How much do you agree or disagree with the following statements?

   Response Options: 1 - Strongly Disagree; 2 - Disagree; 3 - Agree; 4 - Strongly Agree

   a. I know enough about artificial intelligence (AI) to make a chatbot on my own.

   b. I am confident that I can understand AI.

   c. I can figure out how to solve hard AI problems if I try.

4. **Identity**

   a. If I chose to, I could have a job that uses AI.

   b. I see myself using AI in my future job.

   c. I want to use AI in my job.

5. **Persistence**

   a. I would like to learn more about AI in the future.

   b. I would like to take a class in AI.

   c. I would like to join an AI club.

   d. I think I could do work in AI when I grow up.

6. **Prior programming experience**

   Have you ever written a computer program before?

   a. Yes

   b. No

c. Don't Know

Have you ever used: (select all that apply)

a. Block coding (Examples: Scratch, Scratch Jr., Tynker)

b. Robotics (Examples: Lego Robots, Lego Spike, Hummingbird, Root, PicoCrickets, Sphero, Micro:bit)

c. App Programming (Examples: App Lab, App Inventor, Mad-Learn)

d. Graphics, Javascript or web pages/HTML (Examples: Pencil Code, Vidcode, Python Turtle, Grasshopper, Processing)

e. Text-based coding (Example: Python)

f. Conversational agent programming (Example: Dialogflow, AMBY, Alexa skill blueprints)

g. Other (please specify): ____

h. None of the above

7. **Language Background**

Are you a native English speaker?

a. Yes

b. No

c. Not sure

What language(s) do you speak at home? (select all that apply)

a. English

b. Spanish

c. French Creole/French

d. Portuguese

e. German

f. Tagalog

g. Chinese

h. Korean

i. Vietnamese

j. Not Listed: ____

Post Survey

1. What is your first name?

2. What is your last name?

3. **Ability Beliefs**

   Prompt: How much do you agree or disagree with the following statements?

   Response Options: 1 - Strongly Disagree; 2 - Disagree; 3 - Agree; 4 - Strongly Agree

   a. I know enough about artificial intelligence (AI) to make a chatbot on my own.

   b. I am confident that I can understand AI.

   c. I can figure out how to solve hard AI problems if I try.

4. **Identity**

   a. If I chose to, I could have a job that uses AI.

   b. I see myself using AI in my future job.

   c. I want to use AI in my job.

5. **Persistence**

   a. I would like to learn more about AI in the future.

   b. I would like to take a class in AI.

   c. I would like to join an AI club.

   d. I think I could do work in AI when I grow up.

6. **Interest formation**

    a. I want to learn more about conversational AI.

    b. I want to learn more about how conversational AI apps (like Siri, Alexa, Google Home) work.

    c. Time in this class passed quickly while working with AMBY.

    d. I was focused while using AMBY.

    e. Creating a chatbot was exciting.

    f. Creating a chatbot was enjoyable.

    g. Making a chatbot is meaningful to me.

    h. I am proud of the chatbot I created.

    i. I would like to show my chatbot to my friends.

    j. I would like to show my chatbot to my family.

    k. AMBY is something I would like to use at home.

7. **Reflection of the classroom activity (At least 3 sentences)**

    a. What did you learn from the conversational AI lessons and activities?

    b. Did the conversational AI lessons and activities help you understand Science concepts you learn from class? If so, how?

    c. What did you like about the conversational AI lessons and activities?

    d. How could the conversational AI lessons and activities be improved?

8. How old are you?

    a. 10

    b. 11

    c. 12

    d. 13

e. 14

f. 15

g. Not Listed ____

9. What is your gender?

a. Female

b. Male

c. Not Listed ____

d. Prefer not to answer

10. Which of the following racial or ethnic groups do you most identify with?

a. Native American

b. Asian

c. Black or African American

d. Hispanic or Latino

e. White

f. Not Listed ____

g. Prefer not to answer

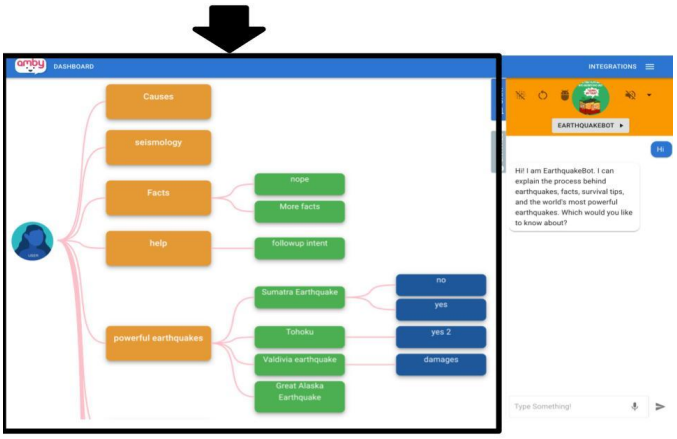
APPENDIX E
CLASSROOM STUDY POST-ASSESSMENT

Next page is the written post-assessment for learners to assess their AI learning from the classroom intervention. Answers highlight in green are the keys.

Dialogs Classroom Study Post Assessment

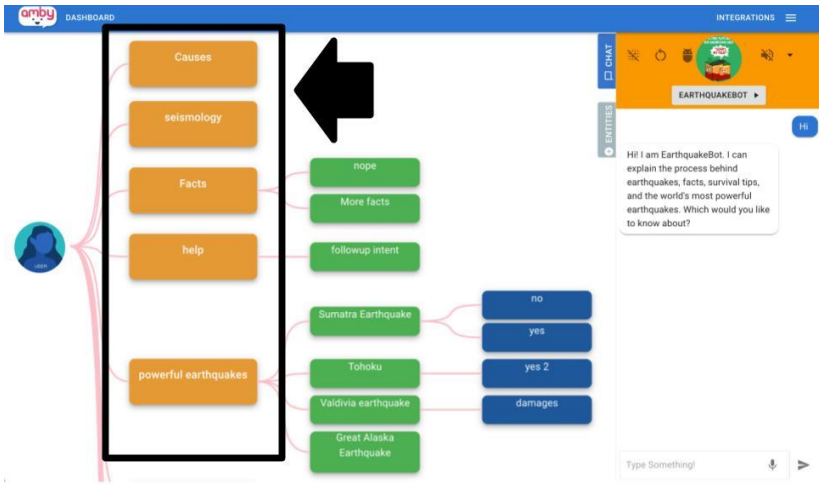
Instructions: Please read each question carefully and circle the best response.

1. Using the image below, what happens inside the large box?



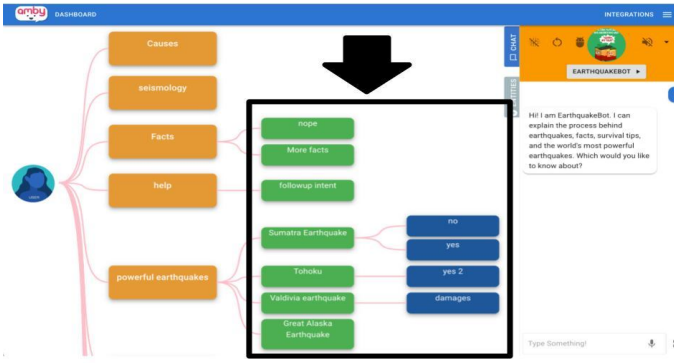
a) The user answers the developer
b) The user talks to the chatbot
c) The developer builds the chatbot
d) The chatbot listens to the user

2. Using the image below to answer the following question. In AMBY, what are the blocks called inside the box?



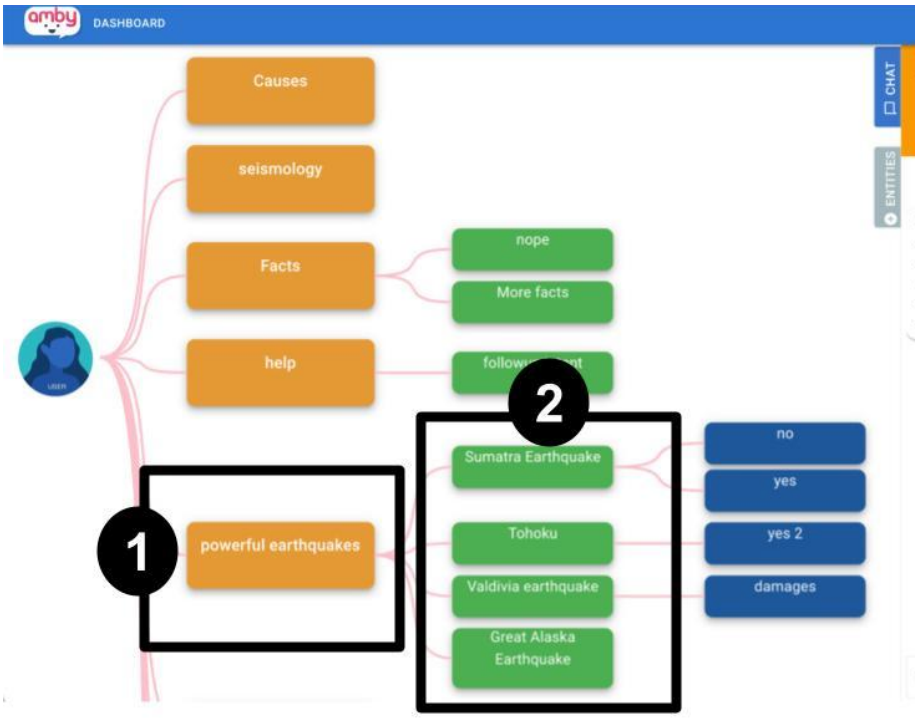
a) Follow-up intents
b) Entities
c) Main intents
d) Default intent

3. Using the image below, what are the blocks called inside the box?



a) Training phrases
b) Main intents
c) Triggers
d) Follow-up intents

4. Using the image below, what is the relationship between the blocks in Groups 1 and the blocks in Group 2?



a) Group 2 gives more information about Group 1
b) Group 1 is a response for Group 2
c) Group 1 and Group 2 both help the user
d) There is no relationship between the two groups

5. A well- made intent needs as many training phrases as possible. Why does AI need to be trained on multiple training phrases for an intent?

a) Because the system (AMBY) needs two training phrases to work
b) To give the chatbot enough data to trigger the correct intent
c) So that the AI will only understand the phrases that programmer used
d) Chatbots can learn training phrases on their own

Use the following scenario to answer questions 6 & 7:

A developer has the following three training phrases for the intent, "Friend's birthday gift recommendation."

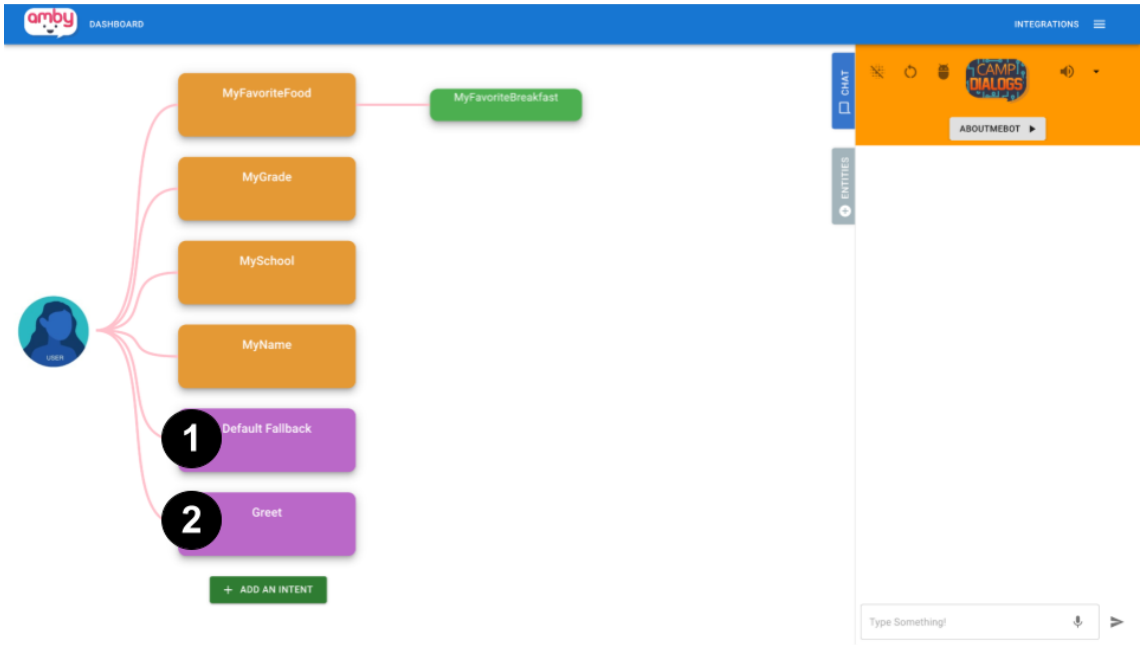
Training Phrases
What gift should I get my friend for their birthday?
I can't decide what to give my friend for their birthday. Any ideas?
I need some ideas to pick out a birthday gift for my friend.

6. What would you suggest as another training phrase for this intent? Write your answer in the box below.

7. Now the intent “Friend’s birthday gift recommendation” has been triggered. What would be a good response for this intent?

a) For a gift, would your friend choose video games, books, or gift cards?
b) I don’t know how I can help with that.
c) That’s exciting! What are you doing for Earth Day?
d) Sure, my favorite basketball player is Lebron James!

Use the following visual for questions 8 - 9.



8. When would the “*Default Fallback” Intent* (represented by 1 on the image) be triggered?

a) When the agent starts the conversation
b) When information about a main intent is provided
c) When there is no intent matching what the user said
d) When the system (AMBY) does not load properly

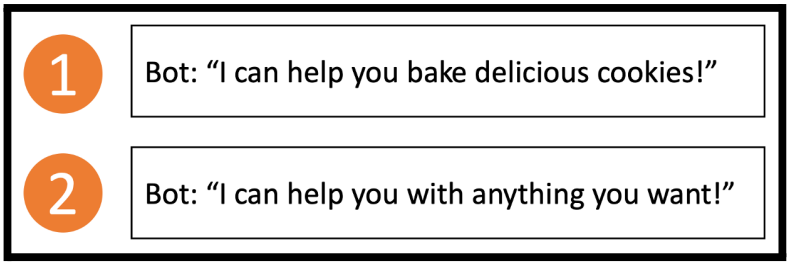
9. When would the agent use the *"Greet" intent* (represented by 2 on the image above)?

a) When the user asks something the AI does not have information about
b) When the agent starts the conversation with the user
c) When the user needs help
d) When the developer has to end the conversation with the user

10. What is the purpose of follow-up intents?

a) To inform the user of the chatbots abilities
b) AMBY does not have enough room for too many main intents
c) To greet the user
d) To allow users to discuss the same topic further

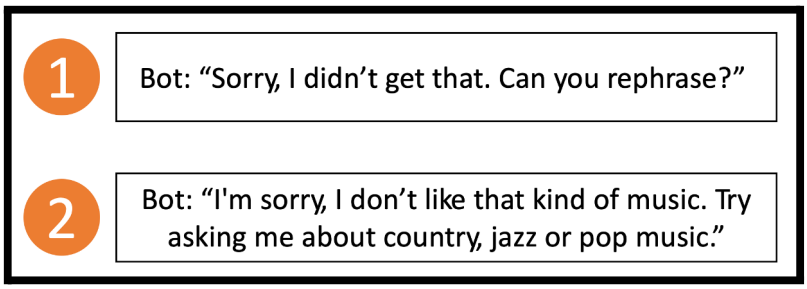
Here are two possible chatbot responses to a user saying "I need help." Use them to answer question 11.



11. Which one is a better conversational design and why?

a. 1, because the bot provides food recipes to the user
b. 1, because it says what the chatbot can help with
c. 2, because it props the user to keep the conversation moving
d. Neither, because they do not offer help

12. Using the information in the box below, which of the following chatbot responses for the *"Default Fallback"* intent is better?



a) 2, because it redirects the users

b) 1, because it because it is shorter

c) 1, because it is a question

d) 2, because it shows the chatbot likes music

13. You are designing a chatbot that will be personalized and friendly, here are two possible chatbot responses to a user asking "Can you recommend a song?" Which one has a better conversational design? Why?

1. **Sure! What kind of music do you like? Country, jazz or pop songs?**
2. **I recommend 'Break Free' by Ariana Grande.**

a. 2, because the user gets an artist recommendation.

b. 1, because the conversation is more interactive and customized to the user.

c. 2, because it does not ask the likes of the users.

d. 1, because it is a longer reply to the user.

14. In a sentence like "I want to book a flight to Paris for tomorrow", which word represents a potential entity related to destination?

a. Tomorrow
b. Book
c. Flight
d. Paris

15. What is an entity in the context of conversational AI?

a. A complete chatbot application.
b. A phrase that the chatbot is trained on.
c. Specific pieces of information that users might provide.
d. The sentiment of a user's message.

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BIOGRAPHICAL SKETCH

Xiaoyi Tian grew up in Songyuan, a city in Jilin province, located in northeastern China. Her passion for education first took root in middle school, inspired by the lasting influence of her teacher Zhao Zhenjie. In 2018, she completed her Bachelor's degree in Management Science at Anhui University. During her sophomore year, she conducted on her very first independent research project with Dr. Jing Li. This experience has further confirmed her desire to pursue a career at the intersection of education and computing.

After her undergraduate studies, Xiaoyi came to Pittsburgh, United States to pursue a Master's degree in Information Science at the University of Pittsburgh, with a specialization in human-centered computing. During this period, she was involved in several research projects and collaborated with experts in the fields of AI in Education and Human-Computer Interaction, including Dr. Erin Walker, Dr. Rosta Farzan, Dr. Jacob Biehl, Dr. Amy Ogan, and Dr. Michael Madaio.

In 2020, she joined the PhD program in Human-Centered Computing at the University of Florida and became a member of Dr. Kristy Boyer's LearnDialogue group to further her research in HCI and education. Her focus is now on introducing Artificial Intelligence to K-12 students and using computational methods to explore linguistic patterns during collaborative learning. She employs a learner-centric approach to understand how students engage with technology in learning environments and aims to design educational technology that support authentic and engaging learning experiences.