Explaining Engagement: Learner Behaviors in a Virtual Coding Camp

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Abstract. Engagement is critical to learning, yet current research rarely explores its underlying contextual influences, such as differences across modalities and tasks. Accordingly we examine how patterns of behavioral engagement manifest in a diverse group of ten middle school girls participating in a synchronous virtual computer science camp. We form multimodal measures of behavioral engagement from learner chats and speech. We found that the function of modalities varies, and chats are useful for short responses, whereas speech is better for elaboration. We discuss implications of our work for the design of intelligent systems that support online educational experiences.

Keywords: Engagement · Underrepresented learners · Virtual camp

1 Introduction

Empirical research has long confirmed that engagement is essential to learning [2, 6]. Although a precise definition of engagement is elusive, researchers agree that it consists of complexly interwoven behavioral and psychological components [7, 15, 17]. Given this critical link between engagement and learning, researchers have created innovations to improve outcomes, particularly through AI systems that detect engaged learning behaviors and intervene accordingly. However these works overwhelmingly consider a narrow view of engagement, classifying learners as overall engaged or not. This does not take into account for a given learner how their engagement might vary across interaction modalities (e.g., speaking out loud versus text-based chatting) and tasks. For example, a learner may appear to be disengaged because they are not actively speaking up. However, in a small group setting they might start to talk more as they become more comfortable. These multiple views are important because, as noted by culturally-responsive engagement frameworks, learner behaviors will differ, as their values and cultural norms differ [2]. A better understanding of how engagement manifests across

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these varying contextual factors is crucial to better design of AI systems, as it can inform what is being modeled and the types of interventions that will be most effective.

Our work begins to fill this gap by understanding the behavioral engagement patterns that emerge in a diverse group of middle school girls participating in an online computer science camp. Our focus in this work is behavioral engagement, which refers to a learner's participation and presence in the environment [7,15]. We focus on behavioral engagement because its indicators, such as attendance or participation, are directly measurable [15]. We use chat and speech signals to represent verbal contributions, such as sharing artifacts built in the camp.

Most closely related to our work is that on detecting learners' engaged behaviors [5,8,9,11,13,14,18]. More limited work has sought to explain the types of engaged behaviors that occur in educational environments, such as participation via help-giving behaviors [1,12], self-regulated learning behaviors [4], or on-topicness and frequency of MOOC posts [18]. Recent work has combined signals to form a multimodal understanding of engagement [10,19]. In an environment most similar to ours, Lin et al. [11] studied an online flipped course. They used a combination of log and behavioral data (e.g., punctuality, camera on versus off). They found that students who watched more pre-lecture videos had better conceptual understanding and higher grades, and students who arrived on time with their cameras on interacted more. These works give a more holistic view of engagement by including multiple modalities in their analysis. However, there is still a gap in describing the various contextual factors that influence engagement (e.g., differences across modalities and tasks).

2 Data Collection and Processing

Participants were ten middle school girls (ages 12-14) from diverse racial backgrounds (four white, one Hispanic/Latina and white, one Asian and white, two Hispanic/Latina, one American Indian/Alaskan Native, and one chose not to report). Nine of the ten learners indicated some form of previous programming experience. Learners were monetarily compensated for their participation. The virtual coding camp took place over three days (two to three hours a day), on Zoom, an online videoconferencing platform (https://zoom.us/). Chats and audio were recorded with Zoom's built-in functionality.

We designed the camp to provide a culturally-responsive, introductory computing experience. Culturally-responsive computing aims to address not only technical literacy, but community, culture, and identity [16]. Led by three facilitating instructors, the camp included activities focusing on both computer science concepts and reflections on power and identity (descriptions shown in Table 1). For coding activities, learners used a custom-built, online, block-based programming interface, where the goal was to use code blocks to control a robotic character.

We utilized data from learner chat and speech contributions. We removed data from time periods without relevant activity (e.g., logging into the session).

Table 1. Description of the categories and number of activities are shown.

Category	#	Description
Active Prompt	2	Respond to prompt via chat
Breakout Room Activity	2	Collaborate in small groups to solve a problem
Coding	6	Individual programming assignments following the lessons
Community Building	6	Get to know other learners
Feedback	3	Give facilitators feedback on how to improve the camp
Lesson	9	Learn computer science concepts and how to implement in coding interface
Movement	3	Move around to increase energy
Power and Identity	11	Reflect on culture and representations of power and identity
Presentation	5	Presentations about robots, coding, and notable women of color in computing
Share Out	6	Share coding creations from Coding assignments

We replaced emojis or emoticons (e.g., `:)`) with the word *emoticon* so they could be included as a single word for analysis. We transcribed the speech data using a third-party service. Two members of the research team quality checked the transcriptions and removed 22 utterances for which the speaker could not be identified. For both modalities, we tokenized words using NLTK [3]. In total, 759 chats and 638 utterances were included in our analyses.

We summarized the signals at the activity level in order to compare behavioral engagement across modalities. To do this, we counted the number of chats or utterances in a given activity, and standardized by the duration (minutes) of the activity. Our final **engagement frequency** metrics were words chatted and words spoken per minute. For each modality, we also calculated a category-level **binary engagement** value as whether the learner engaged at any point during that category (e.g., the learner sent at least one chat).

3 Results and Discussion

The distribution of the proportion of categories in which learners were engaged (binary engagement) is shown in Fig. 1. All learners engaged via chat in at least 50% of the categories, suggesting widespread learner preference for chat. Compared to chats, there was more variability in whether learners spoke aloud. Overall speech was less frequent with 30% of learners speaking in less than half the categories. This finding is unsurprising as there are fewer barriers to chatting than speaking (e.g., no need for a working microphone or quiet space to talk).

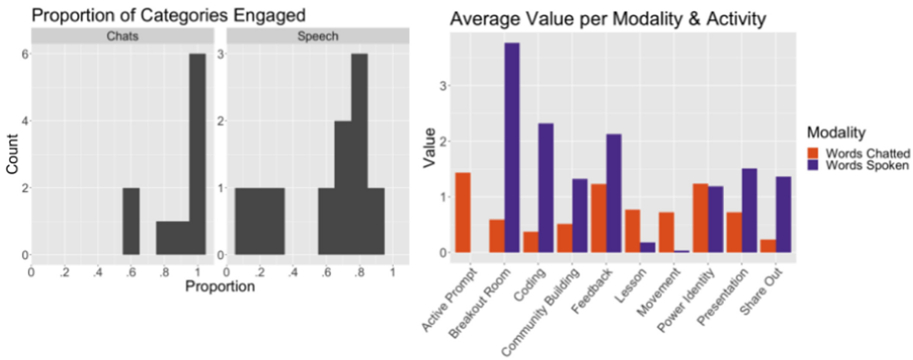

Fig. 1. (Left) For each modality, the distribution of categories in which learners were engaged are shown. (Right) For each activity category, the average words chatted and spoken per minute are shown.

In order to understand how behavioral engagement differs across tasks, we used the engagement frequency metrics to calculate the average words chatted or spoken per minute for each category (Fig. 1). Speech contributions dominate chat contributions for almost every activity, suggesting learners were more verbose when speaking aloud than chatting. We confirmed this finding by calculating the average words per utterance (9.94) compared to the average words per chat (3.58). Taken together with our previous findings, we hypothesize that a frequency-verbosity trade off affects behavioral engagement patterns for chats and speech. As an illustrative example, in a Breakout Room activity, learners collaboratively designed a robot character and provided more in-depth responses aloud than via chat. One learner spoke about hobbies for the robot: "No-no, oddly specific is what makes people actually enjoy... Very specific, quirky things that make you go 'oh, that seems just like what a human would do', is really what brings things together." Another learner added, "Yeah, it gives the robot a personality. It's not just something made in a factory, it has interactions and you can relate to it, in a way." A third learner suggested a robot hobby via chat, "banjo." In this example, the function of the chat was short, quick responses, and learners elaborated aloud. Indeed for the categories where chatting was the dominant contribution modality (Active Prompt, Lesson, Movement), the task at hand required short, quick responses via chat (e.g., an Active Prompt activity was to write conditionals via the chat).

Our findings provide insight into the design of AI in education systems. We show that a one-size-fits all definition of behavioral engagement does not work in practice, as behavioral patterns differed by modality and task. Thus, intelligent systems should consider flexible definitions of engagement that take context into account [7]. Understanding where and why learners are engaging can guide the kinds of interventions that are most appropriate. This is especially important for marginalized learners, whose engaged behaviors might differ [2,7].

Our work has limitations that should be addressed in future research. Our sample size was small, limiting the kinds of statistical analyses we could conduct. Additionally, we focused on behavioral engagement, which is considered to be the product of other psychological processes [15]. Future work should explore the complex interplay between psychological and behavioral components of engagement. That said, this work presents important steps towards understanding behavioral engagement of a diverse group of middle school girls in a virtual computer science camp.

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