Using Quantitative Data to Help Adult Educators Broker Learning

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INTRODUCTION

Recent research examining learning in informal environments reflects a growing recognition of the important role adults play as *learning brokers* by identifying and orchestrating connections to learning opportunities such as access to people, spaces, programs, and information sources (Barron, Martin, Takeuchi & Fithian, 2009; Barron, Gomez, Pinkard & Martin, 2014). Part of adults' capacity to effectively broker learning draws from adults becoming familiar with youth interests and goals (Ching, Santo, Hoadley & Peppler, 2015; Herr-Stephenson, Rhoten, Perkel & Sims, 2011). For adults in formal and informal environments, however, developing this deep understanding about individual youth can be difficult, due to factors such as finite time and high youth-to-adult ratios.

In our research, we aim to investigate how educators develop knowledge about individual youth using a data-driven methodology. Thus, we ask: *How can we use quantitative data to help adult educators broker learning opportunities for youth?*

This paper presents our approach to using survey data about youth interest and log data generated from youth participation in an online social learning network to construct learner profiles and corresponding brokering prompts for educators through visual representations.

THEORETICAL FRAMEWORK

The practice of connecting youth to learning opportunities (i.e., brokering) requires that educators possess knowledge that will enable them to effectively broker learning opportunities to students. Researchers have identified types of knowledge that can inform educators' capacity to broker learning opportunities including knowledge of youth *interests*, *goals*, and *social connections* (Ching et al., 2015). Further, educators may need to be aware of students' attitudes and tendencies toward seeking help and social connections (i.e., their *network* and *help-seeking* orientations) as well as the appropriateness of a given opportunity based on a student's current skillset (Ching et al., 2015). Thus, effective brokering practices require a broad spectrum of knowledge about youth interests, goals, attitudes, and capacities in addition to knowledge of learning opportunities.

In formal learning environments, educators can gather knowledge about students by gauging interest when they present students with topics (Ainley, Hidi, & Berndorff, 2002). Informally, the parent-child relationship and interaction in the home provide parents with opportunities to recognize and nurture emerging interests (Barron et al., 2009). Due to limited face-to-face interaction and high student-to-teacher ratios educators in online and blended learning environments need alternate methods of gathering information about student interests and goals.

One such method of gathering information is to use student interest inventories. For example, Ely, Ainley, and Pearce (2012) developed a web-based software tool called MINE (My Interests Now for Engagement) which enables students to rate their interest and associated affect (e.g., happy, frustrated, excited) for several domains including electronics, history, and photography. Other measures such as the Science Interest Survey have been used to gauge the effectiveness of game-based intervention programs in stimulating student interest (Annetta et al., 2014). Taken together, these efforts highlight a need for an effective, data-driven method of measuring student interests to improve educators' ability to broker learning opportunities for students in online and blended learning environments.

APPROACH: *Using Data to Build Educator Knowledge of Youth*

One way of building knowledge for brokering is to examine data from learning management systems and other online platforms that students use to interact with course material, peers, and adult educators.

Building from prior research, we are exploring ways to enable and enhance educators' capacity to broker youth learning utilizing collected data. To do this, we have identified categories of *educator knowledge of youth* (see Table 1) and ways in which we can use data to support knowledge building and leverage brokering opportunity. For some of these categories, we can gather information by asking students about them directly and explicitly. For example, to understand the *social connections* of youth, we can ask them in surveys to name other youth they regularly go to for homework help. We can also learn about youth *interests* in certain topics using surveys.

In addition to asking youth directly, we can make inferences about certain categories of educator knowledge of youth by using other data sources, such as log data. Participation in online social learning networks can reveal information about youth *social connections* through social network analysis and traces of user interactions; for example, by examining how individual youth comment on and view the work of others. We can learn about the *expertise and prior experience* of youth by looking at records of achievements earned (such as badges) or quality ratings on posted artifacts. We can infer *interests* by applying data mining techniques to the online contributions of youth (e.g., types of artifacts or comments posted, types of resources accessed).

Table 1. Categories of educator knowledge of youth for brokering and potential data sources.

	Social connections *Who are your friends? Who do you go to for help?*	**Expertise and prior experience** *What can you do? What are you working on?*	**Interests** *What are your interests? What do you want to learn more about?*	**Logistics** *What are the opportunities and barriers to participation?*
Explicit *Asking youth directly*	Self-reported social learning networks	Survey measures of expertise and experience	Self-reported interests and identities	Survey queries of measures of home technology access
Inferred *Using automatically gathered data*	Connections between users through online interaction)	Log data counts of breadth and depth of submitted artifacts; virtual badges earned	Metadata of the types descriptors of artifacts, people, and activities viewed	

We note that this initial framework describing types of educator knowledge for brokering is exploratory, and that other types of information about youth play a role in brokering. Our ongoing qualitative research effort is looking for evidence of other salient types of knowledge of youth in addition to the categories already identified. In this paper, we report on how we have explored the use of s*urvey data* that asks youth about their interests and *log data* from an online social learning network to build educator knowledge of youth to support brokering.

RESEARCH CONTEXT

Our inquiry into supporting brokering is situated in a larger study examining educator-student interactions in blended learning environments. Here we focus on adult mentors working with middle school girls in an out-of-school STEM learning implementation. The Digital Youth Divas (DYD) is a blended online and face-to-face program developed and run by the Digital Youth Network at DePaul University. The program is designed to engage middle school girls, particularly those from underserved urban communities who are interested in art, fashion, and design, with activities in computational circuitry and programming.

The goal of the DYD program is to connect with preexisting interests and positively impact girls' STEM-related identities, learning and knowledge outcomes, and learning community. The program includes (1) self-paced, hands-on, project-based curriculum; (2) an online social learning network used in the face-to-face environment but accessible at any time, including scaffolded assignments and resources, individual portfolio spaces, and interaction around submitted work; (3) adult mentorship on and offline.

METHODS

Participants. Girls were recruited to the free 20-week DYD program through flyers and notifications sent to Chicago public schools, advertisements for parents on social media, and emails to parent listservs. Over 100 girls participated (N = 109). Approximately two thirds of girls (65.4%) of girls self-reported as African-American, 20.5% as Latina, 9.3% as white, and the remaining girls described themselves as Asian or mixed-race. They ranged from fourth to eighth graders; 7% of girls were in 4th grade, 24% 5th grade, 31% 6th grade, 29% 7th grade, and 9% 8th grade. The ten female DYD mentors (five lead mentors and five junior-mentors) were undergraduates or recent graduates (in liberal-arts-focused areas of study), most of whom had some prior formal and informal experience working with children.

Data Collection. The DYD program met for three hours once a week on Saturdays at a centrally located downtown university. Data was collected from the 6-month program over the course of the first 3-months (January-March 2016) at multiple levels of analysis including (1) an overview of the entire program through quantitative counts of online participation from user log data (N = 109 girls and 7 mentors, N = 13k log entries) and surveys (N = 90 girls) of interest, access, and experience (adapted from Barron, Walter, Martin, and Schatz, 2010); and (2) individual perspectives from mentors (N = 7) through focus groups during professional development, and informal discussion and semi-structured interviews around practice and design features and visualizations.

Analysis 1. Clustering Youth Interest Survey Data

Girls in the program were given the interest, access, and experience survey the second week of the program. As a way to gather data about the girls' interests, we included a survey item asking them to rate their interest in 12 different design activities and technical practices such as "Programming computers," "Fashion design," and "Fixing or building computers" using a 4-point Likert scale (Not at all interested, A little interested, Interested, Very interested). This item is an adaptation of an interest measure created for the National Center for Women and Information Technology (NCWIT) (DuBow, et al., 2015), with additional interest areas that are relevant to the Digital Youth Divas program.

To understand similar interest patterns of girls in the program, k-means clustering was performed using the responses from this survey item. K-means clustering aims to partition data into k groups based on their response similarity (Finley, & Joachims, 2008). In order to identify the number of clusters (k), the sum of squared errors (SSE) criteria was used, which measures the distance of each point to the cluster center (Chiang & Mirkin, 2010). The distance between the points is computed using Euclidean distance which led us to choose six unique clusters consisting of students with similar interests.

Analysis 2. Interpreting the Results of Clustering Analysis

Taking the results of the clustering analysis, which identified six groups based on interest survey item, we applied a qualitative lens of interpretation to make these results useful to DYD practitioners and designers. Researchers familiar with the DYD goals, context, and curricula reviewed characteristics of the clusters and combined groups that seemed to best identify groups that both mapped onto the DYD model and that accurately reflected the girls in the program. From this process, we identified and described five "Initial Interest Groups" groups (Table 2).

Table 2. Initial Interest Group names and descriptions based on interpretation of clustering analysis.

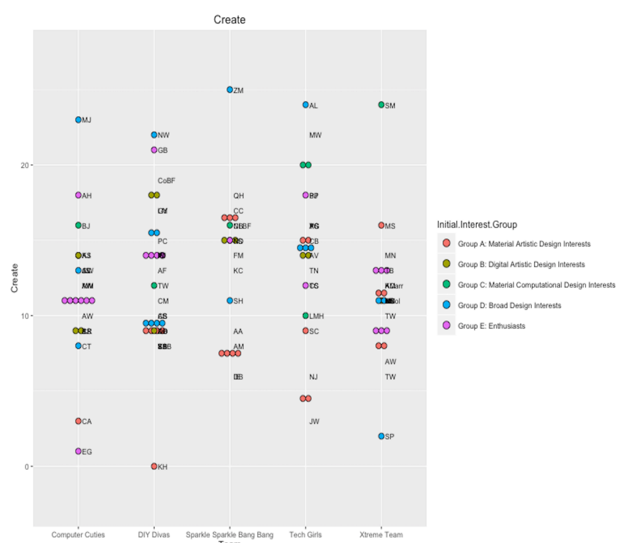
Initial Interest Group	Group Description
Material Artistic Design Interests (clusters 3 and 6, N=29)	Girls who expressed interest in artistic activities using hands-on material design resources, like sewing and fashion, over other types of activities, and who were not very interested in any of the technological practices.
Digital Artistic Design Interests (cluster 1, N=12)	Girls who expressed interest in making and designing with technology, but who not as interested in any of the material design activities like circuitry, fashion, or sewing.
Material Computational Interests (cluster 1, N=8)	Girls who expressed interest in technology activities and practices, and a lot of interest in hands-on computational construction activity like circuitry and innovative technological practices.
Broad Design Interests (cluster 5, N=21)	Girls who express interest in most of the technology activities and practices we asked about, but have a particularly high interest in artistic material making.
Enthusiasts (cluster 2, N=23)	Girls who express high interest in most of the technology activities and practices we asked about, with no obvious preference on the spectrums we established.

RESULTS

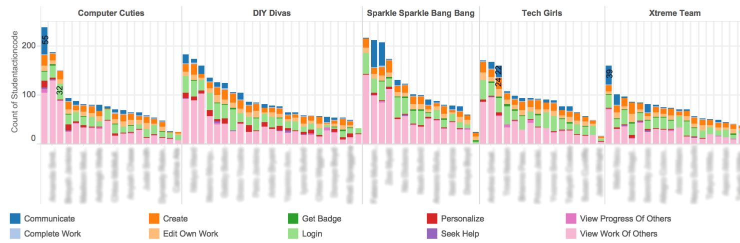
Using the *Initial Interest Group* information, our emerging understandings of how to better enable and enhance brokering using data, we created initial concepts and prototypes, continuing to build on reflections and conversations with mentor practitioners and program designers. We provide a brief description of selected concepts below.

Using *Initial Interest Groups* and log data, a visual representation (violin plot) provides mentors with information about youth interests and activities.

Girls in the program are represented by a dot, and are plotted according to the number of actions that reflect creating and posting media artifacts to the online social learning network. Girls who posted more are plotted towards the top of the graph. The vertical lines indicate the team to which the girl is assigned, and the color of the dot indicates the Initial Interest Group.



This visualization shows girls in the program, organized by team. The bar chart shows the types of activities logged by youth in iRemix; for example, showing counts of *communicating* with others and *creating* and *editing* their own work.



CONCLUSION

In this paper, we describe our approach to using quantitative data to better enable and enhance brokering, with a focus on ways to build *educator knowledge of youth.* Specifically, we are interested in how mentors might derive insights from data about youth interests that support brokering, for example by connecting youth to people and activities within the program that can deepen their interests, or by connecting them to programs or resources outside the program. Future work will involve iterative development of these tools and visualizations, including the integration of information gained from data mining techniques and by working with mentors in the context.

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